ACCELERATING ENERGY INNOVATION: CAN ENERGY EFFICIENCY POLICY MAKE A DIFFERENCE?

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ACCELERATING ENERGY INNOVATION: CAN ENERGY EFFICIENCY POLICY MAKE A DIFFERENCE?

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SUMMARY

The objective of the first essay is to examine the impact of the voluntary environmental policy on technological innovation in household appliance firms. The key hypothesis is that firms participating in the ENERGY STAR program were more likely to innovate in response to the 1997 ENERGY STAR criteria update than firms that did not participate. Because participation in the voluntary environmental policy is not random, a time-varying instrument variable—a participation in the Green Light Program—is used to account for unobserved heterogeneity. NBER patent data from 1990 to 2003 related to the energy efficiency of household appliances is matched with COMPUSTAT to include firm-level financial information. A Poisson fixed effect model with an instrument variable estimator reveals significant evidence regarding the impact of ENERGY STAR on participating firms' patents.

The environmental innovation literature reveals a positive relationship between environmental policy and innovation. However, the impact of the domestic energy efficiency policy on foreign innovation is underexplored. Using global patent data from the European Patent Office World Patent Statistical Database, an identification comes from two quasi-experiments: the Top Runner Program in 1998 and the Energy Policy Act of 2005. We find strong evidence the domestic energy efficiency policy positively affects domestic patenting. In addition, the analysis provides strong evidence the domestic energy policy leads to technological advances in foreign patenting, especially by Japanese inventors. Moreover, we find strong evidence the domestic policy's uncertainty negatively affects domestic light-emitting diode patenting, specifically among Japanese inventors.

The third essay fills the gaps in cognitive process understanding of human behaviors between future gasoline price perception and the willingness to purchase hybrid vehicles. How consumers form future gasoline price beliefs and its impacts on decision making process in underexplored in literature. Using the monthly Michigan Survey of Consumers conducted in July 2008 to November 2008, we pool five cross sections and run a generalized linear model. We find statistically significant evidence that current and long-term future gasoline price perceptions affect the willingness to buy hybrid vehicles. This chapter also shows the long-term future gasoline price perceptions predict better than the short-term future gasoline price beliefs. Understanding the effect of gasoline price on the willingness to buy more fuel-efficient cars has an important policy implication for the gasoline tax and other economic incentives to internalize negative externalities.

CHAPTER 1. INTRODUCTION

1.1 Energy-Efficiency Gap

To achieve sustainable energy in the future, increasing energy efficiency plays a significant role because energy efficiency is well known as the fifth energy resource that promises to solve the energy crisis. The phrase "energy-efficiency gap," coined by Hirst and Brown (1990) refers to the unexploited economic potential of energy efficiency. After the publication of Hirst and Brown's (1990) seminal paper, there has been considerable interest in the energy-efficiency gap. The energy-efficiency gap refers to the difference between observed energy-efficiency investment and the technically feasible, cost-effective alternative (Hirst & Brown, 1990; Brown, 2001). Although there is controversy[1] about the size of the energy-efficiency gap, there is evidence that a sizable energy-efficiency gap does exist and we can pick the so-called low-hanging fruit by using proper policy instruments to close the energy-efficiency gap.

The energy-efficiency gap has several causes. According to Hirst and Brown (1990), the energy-efficiency gap can originate from two causes: structural barriers and behavioral barriers. While behavioral barriers result from individual decision-making regarding end-use energy consumption, structural barriers result from the actions of public and private organizations. Additionally, Jaffe and Stavins (1994) identified market failures and non-market failures as

[1] Allcott and Greenstone (2012) argued that the energy-efficiency gap would be small than most of engineering economy based research has claimed because engineering economy based efficiency studies mostly use McKinsey studies(Granade, Creyts, Derkach, & Farese, 2009) for supply curve of efficiency technologies. Neo-classical economists are skeptical about whether McKinsey report accounted for all relevant costs (Gillingham & Palmer, 2013).

barriers to improving the energy-efficiency gap. A market failure is something inherent in the market that causes the market's allocation of resources to be inefficient. Market failures include asymmetric information, non-competitive markets, and externalities and public goods. On the other hand, non-market failure refers to the reason why the observed behavior is optimal from the point of view of energy users. Non-market failure accounts for uncertainty about future energy prices. These factors can create the energy-efficiency gap for both energy-efficient technology producers and consumers.

1.2 Policy Instruments

Several policy instruments can be implemented to close energy-efficiency gaps (Linares & Labandeira, 2010). First, governments can implement taxes or subsidies to affect the behavior of consumers and firms. Technology standards that set minimum energy efficiency requirements for products can be used as another way to close the energy-efficiency gap. Second, economists prefer to implement market-based environmental policies, such as tradable permits, because market-based approaches are theoretically more cost-effective than command-and-control approaches. Economists have long preferred the market-based approach over regulatory approaches to reduce carbon emissions for economic efficiency (Chen & Tseng, 2011). Third, voluntary information-labeling policies can be cost effective and may resolve some market failures.

Conventionally, the United States has used the command-and-control approach to manage environmental pollutants. The command-and-control approach forces firms to reduce pollution outputs to a certain point regardless of costs (Stavins, 2007). For example, regulations require the installation of pollution-control equipment, and put limits on the number of pollutants produced from manufacturing factories. In addition, Renewable Portfolio Standard (RPS) is a regulatory policy that requires increased energy production from renewable sources. The RPS mechanism places an obligation on electricity supply companies to produce a specified percentage of their electricity from renewable energies (Metcalf, 2009). In the household appliance market, for example, the purpose of the minimum energy-efficiency standard is to remove less efficient products from the market so that overall energy efficiency of products will improve; this has been evaluated as a quite successful policy instrument.

The biggest advantage of the command-and-control approach is that monitoring is easy. Since a regulator directly specifies the allowable level of pollutants, the only thing the regulator needs to do is verify whether firms meet the environmental goals. However, command-and-control has disadvantages as well. First, it is costly to monitor every individual polluting source. Second, it lacks leeway in achieving equal marginal control costs, which makes the policy expensive to enforce.

Information programs also play a significant role in closing the energy-efficiency gap. In the household appliance market, ENERGY STAR is an energy-efficiency program that provides information to consumers and firms regarding energy-efficient technologies. The provision of information could mitigate inefficiencies that arise in an asymmetric information market (Akerlof, 1970). In other words, the role of ENERGY STAR is to help consumers identify more energy-efficient products thereby inducing behavioral changes. The program asks the sellers of highly energy-efficient products to indicate to consumers the quality of their products. With this information, consumers can select highly energy-efficient products instead of products that are not energy efficient.

1.3 Energy Innovation and Energy-efficiency Gap

What is the role of policy in promoting technological innovation to close energy-efficiency gap? Well-designed energy policies can lead to technological innovation. Existing research provides evidence to support this argument. Several scholars (Jaffe & Palmer, 1997; Brunnermeier & Cohen, 2003; Kneller & Manderson, 2012) found a positive relationship between environmental policy and innovation. Building on Jaffe and Palmer (1997), environmental economists took advantage of econometric techniques to estimate the impact of various factors on energy innovation (Jaffe, Newell, & Stavins, 2002; Altwies & Nemet, 2013; Carrión-Flores et al., 2013; Carrión-Flores & Innes, 2010; Keith Brouhle et al., 2013; Jaffe & Palmer, 1997; Lanjouw & Mody, 1996; Brunnermeier & Cohen, 2003; Popp, 2006; Popp, 2005; Horbach, 2008; Horbach, Rammer, & Rennings, 2012; Popp, 2002). Well-designed energy policy leads to technological innovation while poorly designed energy policy inhibits innovation (Managi, Opaluch, Jin, & Grigalunas, 2004).

Academic literature on innovation indicated that several determinants give rise to innovation. Schumpeter's (1934) seminal paper discussed the idea of the size of firms and the market. His ideas influenced subsequent literature, and he argued that the creation of new inventions is pushed through research and development. Additionally, Schmookler (1962) asserted that demand incentivizes innovation. There is a distinction between demand-pull and technology-push arguments as determinants of innovations. Demand pull focuses on the role of consumers while technology push refers to the idea that a new invention is pushed through research and development (Jaffe & Palmer, 1997; Peters, Schneider, Griesshaber, & Hoffmann, 2012; Costantini, Crespi, Martini, & Pennacchio, 2015). Recently, researchers also argued that appropriability, the ability to control and exploit the benefits from innovation, is one of the key drivers of innovation. Furthermore, higher energy prices are a crucial factor in stimulating energy innovation, ceteris paribus, which is known as "Hicks' induced innovation hypothesis" (Hicks, 1932).[2]

Development of energy-efficient technologies can be a promising solution for closing energy-efficiency gap. However, these technologies appear not to be adopted by consumers to a degree that would sufficiently close the gap. Economists have also put a lot of effort to identifying factors that drive or hinder the adoption of energy-efficient products by consumers. In this dissertation, while the first two essays are related to the relationship between policy and energy-efficient technology producers, the third essay is about identifying factors that affect the adoption of energy-efficient products by consumers.

1.4 The First Essay

The objective of the first essay is to examine the impact of energy-efficiency policy on innovation in household appliance firms. Firms must meet the minimum federal standards dictated by the National Appliance Energy Conservation Act (NAECA) in order to sell their products. Furthermore, ENERGY STAR was created in 1992 and assists firms that invest in energy-efficient products, thereby promoting energy-product diffusion to consumers. Figure 1 shows the development of average household refrigerator energy use, volume, and price over time.

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[2] For an empirical analysis, Newell, Jaffe, and Stavins (1999) developed a methodology for testing the hypothesis by estimating a product characteristic of household appliances.

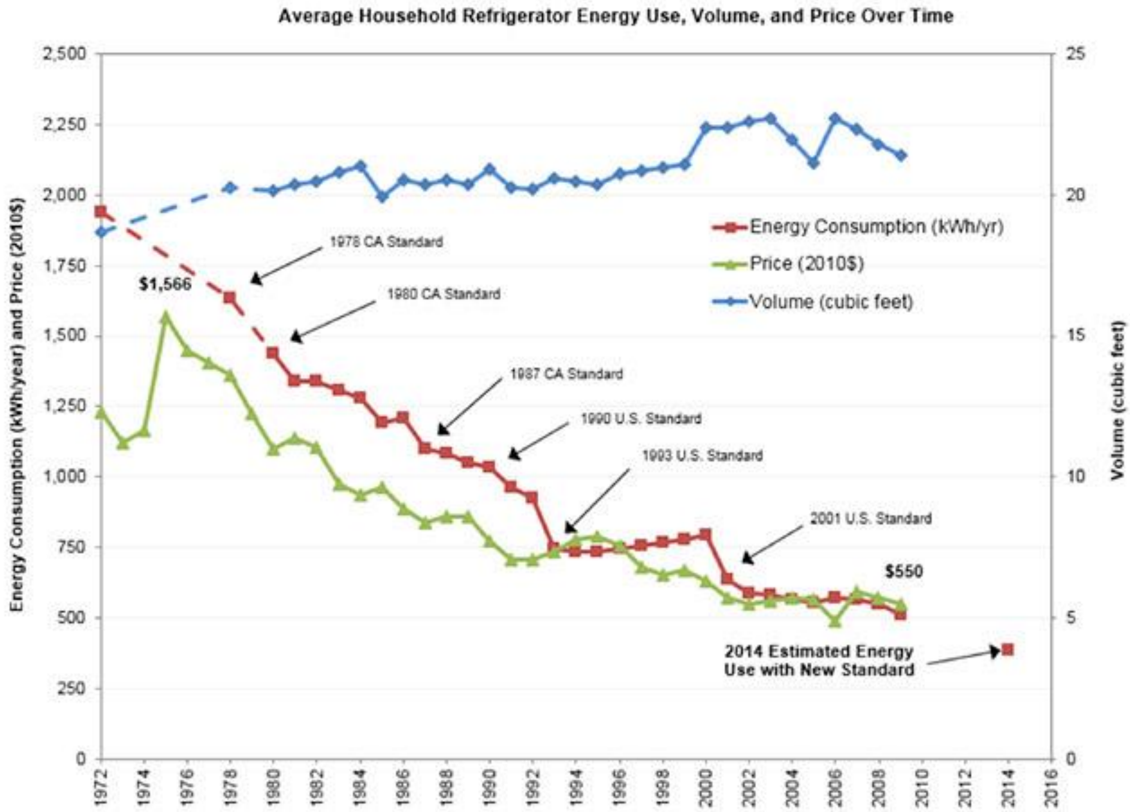

Figure 1. Average Household Refrigerator Energy Use, Volume, and Price over time[3]

Firms have incentives to participate in voluntary environmental regulations in order to avoid more stringent regulation from the government. Some firms have gone above and beyond the threshold of voluntary standards while others barely satisfy the minimum requirement; both reactions send a signal to consumers and the government. When firms achieve the requirements for ENERGY STAR certification, they can raise their prices in order to maximize their profits. However, there is a dearth of research on the relationship between energy-efficiency policy and innovation across firms. Therefore, this chapter investigates why firms participates in voluntary

[3] http://www.aceee.org/blog/2014/09/how-your-refrigerator-has-kept-its-co

environmental programs and what is firms' patenting behavior in response to energy-efficiency policy changes.

From a program evaluation perspective, is a voluntary approach an effective environmental policy instrument? Initially, scholars were interested in the reason why firms participate in voluntary environmental policy (Arora & Cason, 1996). Numerous researchers empirically studied the effectiveness of voluntary programs (B. Howarth, Haddad, & Paton, 2000; Khanna, Khanna, Damon, & Damon, 1999; Pizer, Morgenstern, & Shih, 2008; Bui & Kapon, 2012; Bae, Wilcoxen, & Popp, 2010; Cutter & Neidell, 2009; Kotchen, 2013; Morgenstern & Pizer, 2007). A recent theoretical work by Mason (2013) shows that it is still uncertain whether voluntary labeling programs are an effective policy. This is partly because complications arise when bounded rational consumers, strategic companies, and the government work against each other. Brouhle and Khanna (2006) showed that increasing awareness among consumers of the quality of a product can increase the quality of products, but it could also result in too much product differentiation. Scholars have also shown interest in evaluating the impact of voluntary environmental policy on innovation using patent data (Keith Brouhle, Graham, & Harrington, 2013; Carrión-Flores, Innes, & Sam, 2013a). For example, Keith Brouhle et al. (2013) find evidence that the Climate Wise Program positively lead to environmental patenting. On the other hand, Carrión-Flores, Innes, and Sam (2013b) show that 33/50 voluntary programs deter future environmental technological innovation. Therefore, there is no consensus among researchers regarding the impact of voluntary environmental program on innovation.

1.5 The Second Essay

Both the characteristics of policies and the country-level policy are important factors affecting technological innovation. In the second essay, we use global patent data to investigate how countries' lighting innovation activities respond to domestic or foreign mandatory energy-efficiency policies.

The raw technology for compact fluorescent light (CFL) bulbs and light-emitting diode (LED) bulbs was developed more than 10 years ago, but it was crude; moreover, conventional incandescent light bulbs attracted more consumers and, therefore, producers had incentives to produce more incandescent light bulbs in the market. To increase the innovation and diffusion of more energy-efficient lighting technologies, a policy driver was required to move forward.

Both domestic and foreign energy efficiency policies can affect CFL and LED advancement. Even though the impact of foreign energy policy is relatively small compared to the mandatory domestic energy policy, it is anticipated that we cannot underestimate the effectiveness of foreign environmental policy on innovation.

Furthermore, this chapter investigates the role of policy uncertainty on innovation. Because policy uncertainty discourages innovation, it is expected that domestic policy uncertainty negatively affects domestic patenting.

1.6 The Third Essay

Even though firms produce energy-efficient products, it is now the consumers' decision to adopt and use energy-efficient products. From the perspective of consumers, rational consumers take numerous attributes of a product into consideration when they go shopping for energy-related durable goods. They will choose a product based on different features: brand name, price, durability, and energy efficiency. While energy efficiency is not usually a priority when choosing a product, it can be a feature used for evaluations in consumer product reviews. Consider the following example involving light bulbs. Although policy spurs the innovation of products, causing firms to produce more energy-efficient CFLs and LEDs, their popularity is up to the consumers. Barriers can include technical and consumer barriers. U.S. residents were slow to adopt CFLs. Beginning in the late 1980s, utilities engaged in demand-side management to increase consumer adoption of CFLs but faced technical difficulties. In the late 1980s and early 1990s, CFLs were bulky and their light performance was not good compared to incandescent light bulbs. Therefore, consumers disregarded the innovative technology and tended not to buy expensive CFLs rather than low-cost incandescent light bulbs.

A rational consumer should purchase more cost-effective light bulbs. However, most of us are not rational but rather bounded rational. The notion of “bounded rationality” is useful to explain the slow dissemination of CFL and LED technologies. The term was coined by Simon (1985). He claimed that an economic man uses heuristics to make decisions instead of finding an optimal solution. Simon assumed that, because people are bounded rational rather than naturally rational, individuals can only focus on one or a few things at a time. Thus, people look for satisfactory choices rather than optimized solutions using heuristics (e.g., a rule of thumb). In this regard, bounded rational consumers tend to underestimate the long-term benefits of more energy-efficient technologies due to their high up-front costs. Therefore, the policy discussion of how to better design energy-guide labeling and the ENERGY STAR program is relevant to understanding how to better educate bounded rational consumers. Additionally, utilities provide a rebate if consumers purchase LED bulbs, thus making them more attractive to consumers.

Utilities have also sponsored programs intended to drive consumers to buy CFLs, and retailers have provided rebate and coupon programs.

Unlike the price of electricity, gasoline price is more salient to consumers. Since the 1970s, many economists have examined the impact of gasoline prices on the demand for automobiles. Most found that higher gasoline prices lead to increased demand for smaller, more fuel-efficient cars, especially if higher gasoline prices are sustained (Congressional Budget Office, 2008). The longer gasoline prices remain high, the more likely consumers are to switch to fuel-efficient vehicles. Li, Haefen, and Timmins (2008) showed that high gasoline prices affect the purchase of more fuel-efficient vehicles and speed the scrapping of less fuel-efficient vehicles. It appears that there is a link between gasoline price increases and the willingness of people to consider electric vehicles.

In this regard, we examine what factors affect the consideration of purchasing electric vehicles and how consumers value the price of gasoline in terms of their willingness to purchase hybrid vehicles. We are particularly interested in the impact of future energy-price perception on the willingness to consider hybrid vehicles. It is plausible that consumers tend to form future gasoline price beliefs and then make a vehicle choice. Previous literature assumes no change in future forecast assumptions because future gasoline prices are hard to predict. In this chapter, we test the question of future beliefs are better indicators of consumers' willingness to buy hybrid or plug-in hybrid vehicles.

CHAPTER 2. INNOVATION UNDER THE ENERGY STAR PROGRAM

2.1 Introduction

What role do voluntary environmental policies play in determining firms' innovation? The impact that such policies have on innovation is ambiguous because of two opposing effects: signaling and innovation. The signaling effect of a voluntary environmental policy hinders innovation because firms send signals to the government that they anticipate loose environmental policies in the future; they are thus less likely to innovate. Even though a voluntary environmental policy is less stringent than a mandatory environmental policy, firms may find ways to improve the energy efficiency of their products or use less energy to make those products. Depending on the relative sizes of the two effects, participating in the voluntary environmental program may or not lead to technological innovation. It is empirically challenging to tease out these two effects.

The objective of this paper is to investigate the net effects that ENERGY STAR participation has had on household appliance firms' innovation behaviors using patent data. We examine why firms participate in the ENERGY STAR program, and which of the participating firms is actively innovating. The ENERGY STAR program can be complementary or substitutionary to mandatory energy-efficiency mandates that create incentives for firms to make innovations in energy efficiency.

The first objective of this chapter is that product innovation in the household appliance industry has been relatively understudied. Numerous researchers have paid attention to the consumer side of ENERGY STAR, but relatively few studies have examined regarding the manufacturer side of product innovation. Taylor, Fujita, and Dale (2012) conducted a pilot study on the dynamics of innovation and energy efficiency policies. They described the general relationship between the rate and direction of technological change in the household appliance industry. Their paper focused on several leading firms (Maytag, Electrolux, Whirlpool, and General Electric) because those firms have dominated the household appliance market. However, a limitation arises from their neglect of other firms' patenting behaviors. In this paper, we seek to fill that gap.

The second objective of this paper is to provide evidence of the relationship between voluntary environmental programs and technological innovation. A body of literature examines the relationship between energy policy and innovation. Building on Jaffe and Palmer (1997), scholars have taken advantage of the econometric technique to estimate the impacts of various factors on energy innovation (Altwies & Nemet, 2013; Jaffe, Newell, & Stavins, 2002). Particularly, most of the literature relies on R&D expenditures or patent data to assess this relationship. Jaffe and Palmer's (1997) seminal study investigates the relationship between total R&D expenditures (or the number of patent applications) and pollution abatement costs. Subsequently, numerous studies have found a positive relationship between innovation and environmental regulation (Arimura, Hibiki, & Katayama, 2008; Brunnermeier & Cohen, 2003; Lanoie et al., 2011; Popp, 2003, 2006b). One study emphasizes the negative relationship between environmental regulation and innovation; for example, the increased age of capital in U.S.

electric utilities in the 1970s (Nelson, Tietenberg, & Donihue, 1993). However, their study is not considered to be properly designed as a regulation that would encourage innovation.

In general, findings on the effectiveness of voluntary environmental programs are mixed. Innes and Sam (2008) found that the effectiveness of the 33/50 program[4] only lasted for the first year of the program. Carrión-Flores, Innes, and Sam (2013) even argue that the 33/50 program deters future innovation. However, it is possible for firms to learn better technological options by participating in voluntary environmental programs. Contary to other voluntary environmental programs, ENERGY STAR program is generally considered to be a stringent program, and it appears to be an effective voluntary program (Fischer & Lyon, 2014). After becoming an ENERGY STAR partner[5], a firm agrees to measure and track energy usage, implement energy performance strategies, and further educate staff and the public about its achievement. It could be the case that ENERGY STAR may spur the innovation of ENERGY STAR partners. Since the ENERGY STAR program expanded to include refrigerators in 1997, numerous firms have started to become ENERGY STAR partners, which may positively affect the patenting behavior of household appliance firms, especially ENERGY STAR participating firms.

Previous literature[6] emphasized that the decision to participate in a voluntary program is random and there is no systematic difference between the treatment group and control group (Khanna & Damon, 1999). If we use a traditional difference-in-differences estimation method to tease out the impact of the ENERGY STAR on innovation, endogenous problems could arise. To avoid this, Pizer, Morgenstern, and Shih (2008) used a difference-in-differences estimation and

[4] The 33/50 program was the EPA's first effort to reduce pollution by regulated firms initiated in 1991.
[5] https://www.energystar.gov/buildings/about-us/become-energy-star-partner
[6] For reviews of this literature, see Lyon and Maxwell (2002) and Morgenstern and Pizer (2007).

propensity score matching technique where there is no selection bias on unobserved characteristics. This method allows for overcoming observed differences between participants and non-participants.

Due to there being a relatively small number of firms[7], we employ a two-stage estimation approach instead of using difference-in-difference and propensity score matching techniques. In a nutshell, we find suggestive evidence of the impact of ENERGY STAR program on household appliance patenting. Unlike other no-significant results of the effectiveness of the other programs in the previous literature, it is attributed to the minimum energy efficiency standard which may kick unqualified products out of the market and push technology frontiers.

The rest of the paper is organized as follows. First, we provide the historical background of energy policy related to household appliances. Second, we describe the theoretical argument and literature review. Third, we estimate and discuss the results of the impact of ENERGY STAR on innovation using a two-stage model: a participating equation and patenting equation. Finally, we discuss the implications and then conclude.

2.2 Background

The energy crisis in the 1970s led to the implementation of energy efficiency standards. States such as California, Massachusetts, and New York led the way. For example, California passed legislation to create energy efficiency standards for refrigerators in 1978 (ACEEE, 2014). The California Energy Commission subsequently updated these standards in 1980 and 1987. As

[7] We identify firms using patent data. Someone might argue that using NAICS codes would be more appropriate to identify relevant firms, but it raises the issue of low matching ratios among patent data, NAICS codes, and COMPUSTAT. So we use NBER patent data to discern relevant firms.

a consequence, the annual energy consumption of refrigerators in the state gradually decreased. However, states had different types of regulations, and companies did not want to comply with various regulations. Therefore, companies called for a unified federal standard (Lester & Hart, 2012). California's success provided the impetus for the implementation of federal energy efficiency standards. In 1987, President Reagan signed national legislation to finalize the federal standards for products. Following that, the Department of Energy updated the federal standards for refrigerators in 1990, 1993, 2001, and 2014.

The Federal Trade Commission required companies to add Energy Guide labels on their household appliances to inform consumers of the estimated annual operating costs of those products. These estimates were based on the national average price of electricity. Federal standards varied depending on the configuration and the size of the refrigerator.

The federal energy efficiency standards spurred firms' product innovations because firms had to satisfy the requirements. Levine, Koomey, McMahon, Sanstad, and Hirst (1995) showed that the net benefit of the federal minimum energy efficiency standards enacted in 1994 was about $45 billion. Companies challenged themselves to develop technologies with greater energy efficiency—including better insulation, more efficient compressors, and improved heat exchangers. For these reasons, experts have viewed these regulatory policies as some of the most successful energy efficiency policies (Brown, 2001).

To promote the diffusion of energy-efficient products and assist companies that were investing in such products, ENERGY STAR was created in 1992. ENERGY STAR is a voluntary program that provides information about energy-efficient technologies to consumers and companies; the program thereby corrects the informational asymmetry between firms and consumers. Sellers with highly energy-efficient products are asked to indicate the quality of their products to consumers through this program. Thus, informed consumers can select these highly energy-efficient products instead of less efficient products by looking for the ENERGY STAR logo on a product's label. This program is successful in reducing energy consumption and greenhouse gas emissions (Sanchez, Brown, Webber, & Homan, 2008). Joiner & Laux (2008) find that ENERGY STAR partner firms have a competitive advantage compared to non-ENERGY STAR partners.

ENERGY STAR includes household and commercial appliances, such as air conditioners, heat pumps, and refrigerators. Several revisions have been made to the ENERGY STAR criteria for refrigerators since 1992. On January 1, 2003, all refrigerators and freezers greater than 7.75 cubic feet in volume were required to be 10% more energy efficient than the minimum federal standard to be ENERGY STAR certified. Products less than 7.75 cubic feet in volume had to be at least 20% above the federal minimum standard to receive the certification. In 2004, the criteria for full-sized refrigerators rose to 15% in 2004 and to 20% more in 2008. The latter version of the standard (version 4.1), remained in effect until September 15, 2014, [8] when the new ENERGY STAR criteria for residential refrigerators took effect. Table 1 summarizes energy policies that may positively affect the patenting behavior of household appliance firms.

[8] http://www.energystar.gov/index.cfm?c=refrig.pr_crit_refrigerators

Table 1. Energy policies that may impact innovation of household appliance firms[9]

Year	Events
1990	First federal refrigerator efficiency standards enacted
1992	Energy Policy Act signed; EPA ENERGY STAR program is created
1993	Federal refrigerator standards are updated; Super-Efficient Refrigerator Program(SERP) Golden Carrot strategy announced
1997	EPA/DOE Energy Star program expanded to include refrigerators
2001	Federal refrigerator efficiency standards are updated
2007	Energy Independence and Security Act of 2007 (EISA) signed; requires DOE final rule on 2014 refrigerators by end of 2010

In the household appliance market, firms strategically compete to maximize profits and increase market share. Increasing the number of households with energy-efficient products will, over time, reduce overall household energy consumption. As a result, households will spend less on energy, allowing them to spend more on other goods and services. From the firms' viewpoint, they will incur upfront costs to improve the energy efficiency of their products and thus lose short-term profits. However, firms can increase their long-term profits by selling a greater volume. Economic theory indicates that a firm strategically determines the price of its products to maximize profits. Houde (2014) used product-level transactional data from the U.S. refrigerator market to demonstrate that firms clustered their performance around the certification requirement and thereby maximized their profits. Houde (2014) conducted a welfare analysis of ENERGY STAR, but he did not address the relationship between environmental policy and innovation which is underexplored.

9 Source: Department of Energy, 2010; Deumling, 2009; Taylor, 1995

Economic theory indicates that a club members share a common value and enjoy benefits after joining voluntary programs excluding non-club members (Buchanan, 1965; Kotchen, 2012). Once a firm participates in the program, a firm decides whether to continuously introduce ENERGY STAR products or to shirk rules on ENERGY STAR, depending on enforcement and monitoring mechanisms (Prakash & Potoski, 2006) and a firm's resources (Hart, 1995).

Since the United States is a big market, both domestic and foreign firms have an incentive to file a patent application. For example, firms must meet the minimum federal standards dictated by the National Appliance Energy Conservation Act (NAECA) to sell their products in the United States. Additionally, firms have incentives to participate in voluntary environmental regulations in order to send signals to both consumers and the government. Firms hope to sell more products by sending a green signal to consumers. This is called the signaling effect. Firms may hope to escape more stringent regulation from the government by sending earlier signals. Or a firm may have an incentive to innovate in order to satisfy the threshold of voluntary standards or even more. It is therefore possible for U.S. and foreign companies to act differently in order to meet the ENERGY STAR program. For example, foreign companies are more likely to make products higher than their minimum standards. The reason why foreign firms exceed ENERGY STAR standards can be explained by high transaction costs: high processing fees, a risk of ENERGY STAR certification rejection, and change in policy uncertainty. Here we expect to see a differential impact of the policy on domestic or foreign firm innovation.

2.3 Methods

2.3.1 *Model Specifications*

Building on Brouhle, Graham, and Harrington (2013)'s model specification, we construct a two-stage model to estimate the impact of ENERGY STAR on innovation. Ideally, we should account for unobserved heterogeneity, find time-varying instruments, and use a fixed effect Negative Binomial estimator.

First, we construct a firm participation equation. If a firm expects a net benefit, a firm would participate in the ENERGY STAR program. This equation specifies factors that are expected to affect a firm participation in the ENERGY STAR program. Similar to Brouhle, Graham, and Harrington (2013)'s model, we model a firm's net benefit of participation in the ENERGY STAR as follows:

$$\mathrm{D_{i,t}}^* = \beta_1 \mathrm{X_{1i.t}} + \varepsilon_{\mathrm{i,t}} \tag{1}$$

where $D_{i,t}$ is a firm's net benefit for firm i in year t, $X_{1i,t}$ is a vector of independent variables for firm i in year t. β is a vector of parameters we estimate, and $\varepsilon_{i,t}$ is residuals. Table 2 shows a list of dependent and independent variables. Since we cannot measure net benefits of participating, we proxy this with a binary participation decision.

$$D_{i,t} = 1 \ if \ D_{i,t}{}^* > 0$$

$$=0 \text{ otherwise} \tag{2}$$

It reduces to the form and we estimate it using a logit model.

$$\mathrm{D_{i,t}} = \mathrm{F}(\beta_1 \mathrm{X_{1i.t}}) + \mathrm{u_{i,t}} \tag{3}$$

A firm-level patenting equation is as follow:

$$Y_{i,t} = \alpha D_{i,t} + \beta_2 X_{2i,t} + \varepsilon_{2i,t} \tag{4}$$

Where $Y_{i,t}$ is energy-related household appliance patents by a firm i and year t, $D_{i,t}$ is a participation in the ENERGY STAR program, $X_{2i,t}$ is a vector of exogenous variables, $\varepsilon_{2i,t}$ is random errors.

There might be an endogenous problem in equation (4) even after controlling for fixed effects. For example, we could have unobserved factors that affect both a participation decision and a patenting decision. Firms with higher patent propensity are more likely to participate in ENERGY STAR Program, i.e., a sample selection bias can occur. So, we conduct a Hausman test for endegeneity[10] and there are some omitted variables biases in the regression.

In order to overcome the potential endogenous problem in the equation, we follow two approaches addressed in Brouhle et al., (2013). The first approach is to control for unobserved time invariant effect by using fixed effect panel model estimation. This overcomes the potential unobserved heterogeneous effects across firms. For example, "green" managers, engineers, or lawyers may affect both the decision to participate in the ENERGY STAR program and the patenting equation. Early participants in ENERGY STAR partners and late participants in ENERGY STAR partners may behave differently.

The second approach is to control for an unobserved time variant effect by using an instrumental variable. In this chapter, participation in the Green Light program[11], which was a precedent of the ENERGY STAR program, may affect the decision to participate in the

[10] Prob > chi2 = 0.0348

[11] The Green Light Program was later integrated into ENERGY STAR.

ENERGY STAR program but may not affect energy-related household appliance patents. Since the purpose of the Green Light program is to encourage firms or organizations to install energy-efficient technologies, the motivation for a firm to develop innovative energy-related household appliance technology is weak. The rationale for the valid instrumental variable is that the Green Light program is not intended to encourage energy-related household appliance patents directly, but through participation in the ENERGY STAR program. In order to check the validity of the instrument variable[12], we conduct an F-test on the instrument to see if the instrument is jointly significant in the endogenous variable (Cameron & Trivedi, 2010).[13] We find that a participation in the Green Light program is a significant predictor of participation in the ENERGY STAR program.

Because the number of patents is a dependent variable, we employ a Poisson model and use a generalized method of moments (GMM) estimator. As we detect an over-dispersion problem in the count model, we prefer to use a negative binomial model. However, a negative binomial model cannot adequately account for the endogeneity issue in this paper, so our main estimation is an IV Poisson model with fixed effects and to check the robustness of the models using a negative binomial model.

[12] An alternative instrument variable might be brand name book values (advertising expenditure/bookvalue of the firm) (Wang, 2013). However, it does not pass the F-test.

[13] Conditional estimator is always safe when $T < 20$ a unconditional estimator has a negligible amount of bias for $16 \le T < 20$. The bias in the unconditional estimator grows as T decreases (Coupé, 2005). Since T=14, we also use conditional logit fixed effect model to check the robustness of the instrumental variable by allowing for clustered by industry-robust standard errors. In this case, the Chi2 statistics is 109.05.

Table 2. A list of variables

Variable	Obs	Mean	Std. Dev.	Min	Max	Participation Equation	Patenting Equation
Dependent variables							
ES_year	345	0.17	0.38	0	1	X	
No. of patents(by year and firm)	345	3.13	5.04	0	30		X
Independent variables							
greenlight	345	0.24	0.43	0	1	X	
ROA-Return on Assets=net income/total assets	343	5.16	7.05	-26.42	32.31		X
DTA-debt to assets	343	0.15	0.09	0	0.45		X
employee: three-year moving average	309	4.01	1.83	-1.41	6.64	X	X
Capital expenditure: log of the average of a firm's past three years capital expenditure	320	6.12	2.29	-1.41	10.37	X	X
R&D expenditure: log of the average of a firm's past three years expenditure	312	5.66	2.31	-2.50	9.05	X	X
Beverage and Tobacco Product Manufacturing	345	0.04	0.20	0	1		X
Chemical Manufacturing	345	0.23	0.42	0	1		X
Machinery Manufacturing	345	0.08	0.27	0	1		X
Computer and Electronic Product Manufacturing	345	0.22	0.42	0	1		X
Electrical Equipment, Appliance, and Component Manufacturing	345	0.20	0.40	0	1		X
Transportation Equipment Manufacturing	345	0.14	0.35	0	1		X
Miscellaneous Manufacturing	345	0.01	0.12	0	1		X
Others	345	0.07	0.25	0	1		X
Germany	345	0.05	0.21	0	1		X
Italy	345	0.03	0.16	0	1		X
Japan	345	0.24	0.43	0	1		X
South Korea	345	0.03	0.18	0	1		X
United Kingdom	345	0.05	0.22	0	1		X
New Zealand	345	0.01	0.12	0	1		X
Switzerland	345	0.04	0.20	0	1		X
United States	345	0.54	0.50	0	1		X

Notes:

1. The North American Industry Classification System (NAICS) 2002

2. We also use one-year and two-year lags to check the robustness of the models.

2.3.2 *Construction of data*

Patent counts are frequently used as a measure of innovation. Of course, not all firms decide to patent their innovations (Cohen, Nelson, & Walsh, 2000), and thus patent counts are not a perfect measure of energy innovation output.[17] However, they are generally considered one of the best energy innovation outputs.

Previously, Taylor, Fujita, Dale, and McMahon (2012) identified energy-efficient patents related to refrigerator using U.S. Patent Classification (USPC) and four major players including mergers and acquisitions: General Electric, Whirlpool, Electrolux, and Maytag. They identified 64 energy-related patents for refrigerators between 1976 and January 17, 2011, out of a total of 1,060 refrigerator patents. There are two possible caveats to this search method. It may omit relevant patents filed by small firms, and therefore we consider their results to be an under representation of the entire scope of refrigeration innovation. More broadly[18], to better define energy-efficient technological developments in household appliances, we also refer to the recent two level keywords search methods (Barbieri & Palma, 2016).

In this paper, we combine two papers' method which has a broader scope than the four major manufacturers.[19] We collected the patent data to analyze firm innovation behaviors related

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[17] A discussion of the relationship between patent data and energy innovation output is well documented in Popp (2005)'s paper.

[18] An alternative way to identify firms is to use Euromonitor Passport database, a global market information database, but the database does not include non-brand firms. Thus, we rely on the two level keywords search methods to identify relevant firms.

[19] Barbieri and Palma (2016)

First-level keywords: (((energysav$ OR energy efficien$ OR energy conservation OR high efficien$ OR low energy OR low-energy OR low electricity consumption OR energy reduction OR energy economis$ OR energy economiz$ OR energy performanc$ OR less electric energy OR less electricity OR less energy OR energy use manage$ OR energy AND use control$ OR energy manage$) AND (residen$ OR hous$ OR domestic OR hom$ OR dwellin$ OR famil$)).TIAB.)-->399

Second-level keywords: (refrigerator OR refrigerators OR fridge OR fridges OR washingmachine$ OR dishwash$).TIAB. -> 5344

Taylor, Fujita, and Dale (2013)

to refrigerator energy efficiency gathered from the CASSIS[20] (USPTO) and matched with National Bureau of Economic Research (NBER) patent database[21] (Hall, Jaffe, & Trajtenberg, 2001) using patent number. Additionally, we match patent data with COMPUSTAT's financial information using a Global Company Key (GVKEY).[22] We can identify firms using NAICS codes, but one concern is that we may not obtain enough control variables.

We matched the retrieved patents to the ENERGY STAR partner list. [23] It is assumed that the ENERGY STAR partner list is the most up-to-date proxy for ENERGY STAR participating firms. One caveat of this database is that we could not distinguish the participating year of the firm, so we manaully found the year of firm participation, which is shown in Table 5. In addition, data on Green Light participating firms[24] was found in the Environment Protection Agency (EPA)'s Green Lights Annual Reports.

It is not a complete list of ENERGY STAR participants over the course of the years because a firm can go in and out of the ENERGY STAR program. For simplicity of analysis, we ruled out this possibility. We assume that ENERGY STAR partner does not withdraw its membership because a firm can maintain its membership as long it has at least one eligible

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((energy AND efficiency) OR (appliance) OR (household) OR (refrigerator) OR (cooler)) AND (62/$)).CCLS. ---->3220

[20] CASSIS is a stand-alone machine that includes US Patent and Trademark Office database (Utility patents: Jan, 1969 to Apr, 2010).

[21] https://sites.google.com/site/patentdataproject/Home/downloads

[22] GVJEY is a unique six-digit number key assigned to each company in COMPUSTAT database.

[23] http://www.energystar.gov/index.cfm?fuseaction=ESTAR_PARTNER_LIST.showProductSearch&s_code=ALL&partner_type_id=MANUFACTURER&cntry_code=ALL&award_search=N

[24] Green Light participating firms: 501 KK Toshiba, Amana Refrigeration Inc, Carrier Corporation, Coca Cola Botting Works Co, Gen Electric Co, Maytag Co, and Whirlpool Corp.

product. If a household appliance does not satisfy ENERGY STAR requirements, a certification body (CB) reports to the Environmental Protection Agency (EPA) and shares with other CBs through an internal account which is not publicly available on the ENERGY STAR website. Once again, even though one product may be disqualifed over the course of years, it does not necessarily mean that a firm discontinues its ENERGY STAR partnership. So, our assumption is valid.

We dropped any firm that had less than 5 patents from the sample.[26] This resulted in 1,311 patents, including 444 patents by ENERGY STAR participating firms and 867 patents by non-ENERGY STAR participating firms. Figure 2 illustrates the number of energy-related and non-energy-related household appliance patent applications.

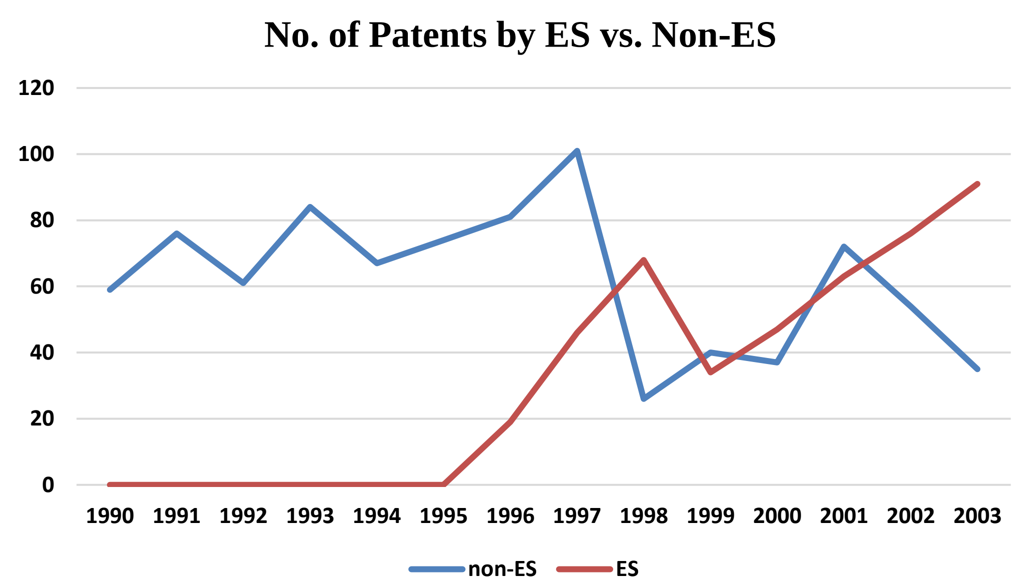

Figure 2. Number of Patent Applications by ENERGY STAR/non-ENERGY STAR firms

[26] We relax this assumption later to check the robustness of models.

To identify where R&D occurred, we used the location information of the assignee. Figure 3 shows the number of patent applications by the assignee's country of origin from 1990 to 2003. United States inventors accounted for about 56% of total patent applications. South Korean inventors accounted for 22%, followed by Japanese inventors.

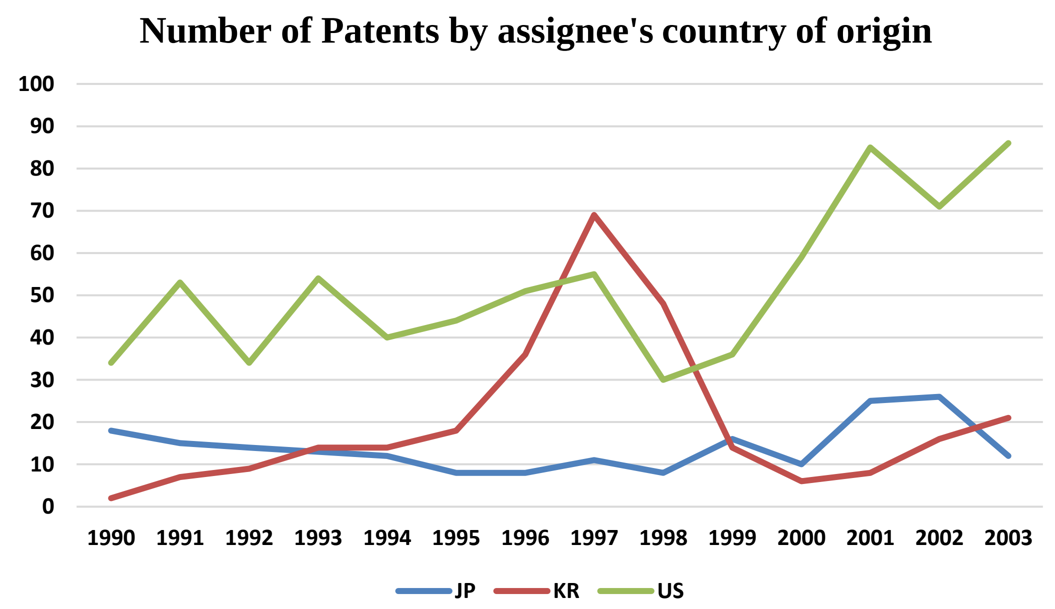

Figure 3. Number of patents by assignee's country of origin

The identification of year of participating in Green Light program comes from the Green Light program reports from 1992[27] to 1996. Each year, a report introduces a new member. A

27 https://nepis.epa.gov/Exe/ZyNET.exe/91012HSE.TXT?ZyActionD=ZyDocument&Client=EPA&Index=1991+Thru+1994&Docs=&Query=&Time=&EndTime=&SearchMethod=1&TocRestrict=n&Toc=&TocEntry=&QField=&QFieldYear=&QFieldMonth=&QFieldDay=&IntQFieldOp=0&ExtQFieldOp=0&XmlQuery=&File=D%3A%5Czyfiles%5CIndex%20Data%5C91thru94%5CTxt%5C00000027%5C91012HSE.txt&User=ANONYMOUS&Password=anonymous&SortMethod=h%7C-&MaximumDocuments=1&FuzzyDegree=0&ImageQuality=r75g8/r75g8/x150y150g16/i425&Display=hpfr&DefSeekPage=x&SearchBack=ZyActionL&Back=ZyActionS&BackDesc=Results%20page&MaximumPages=1&ZyEntry=1&SeekPage=x&ZyPURL

sample of the report's front page is attached in . We manually identify a list of firms and year of participation.[28]

Table 2 shows variables used in both the participation equation and the patenting equation. Once again, we use the number of patents by a firm each year. In the ENERGY STAR participation equation, an instrumental variable is Green Light[29], which is a binary variable that indicates whether a firm participated in the Green Light program.

2.3.3 A Participation Equation

In a participation equation, DeCanio and Watkins (1998) addressed several factors that affect the decision of firms to participate in the Green Light program: large firms, higher earnings/share and higher price/earnings. Therefore, we include in the model the number of employees and firm financial information: Return on Assets and Debt to Assets. Koehler (2007) pointed out several factors influencing participation in voluntary environmental program: final goods producers, consumer pressure, and higher advertising expenditures per unit sales. Several other variables can be included, but we do not include them in models because most ENERGY STAR partners are final goods producers as well. It is also not easy to obtain entire advertising expenditures for companies over the course of years.

2.3.4 A Patenting Equation

[28] Green light participating firms in 1992: 501 KK TOSHIBA, AMANA REFRIGERATION INC, CARRIER CORORATION, COCA COLA BOTTLING WORKS CO, GEN ELECTRIC CO, MAYTAG CO, and WHIRLPOOL CORP

[29] Howarth, R. B., Haddad, B. M., and Paton (2004) showed that over 2,300 organizations participated in the Green Light program and they achieved about 40 percent energy reduction.

In a patenting equation, firm-level financial information is included in my model to measure firm profitability and uncertainty. Return on Assets, which is net income divided by total assets, is a measure of resource availability of a firm (Russo & Fouts, 1997). Debt to assets is a measure of financial risk (Arora & Cason, 1995). Much previous literature emphasized the significance of a firm's technical capacity on maximizing energy efficiency of firms (Matisoff, 2010; Stafford, 2012). Since capital intensive firms are more likely to file patent applications (Carrión-Flores & Innes, 2010), we include capital expenditure, which is measured by the log of the average of a firm's capital expenditure for the past three years, normalized by the average of number of employees for the past three years. We also include R&D expenditure which is measured by the log of the average of a firm's past three years' R&D expenditure, normalized by the average of number of employees for the past three years. Since capital and R&D expenditures are highly correlated, we do not both include in the model. We separately include the variable interchangeably to check the robustness of the model.

Finally, we have several control variables. We include a three year moving average of the number of employees to control for the size of a firm. Industries can have different incentives to file patent applications, and Lange (2009) argues for the importance of industries examining voluntary environmental programs, so we include a NAICS industry code dummy variable. Environmental innovation is spurred by the anticipated regulation of energy efficiency policy as well, so we include a year fixed effect. We also include a firm fixed effect to control for time-invariant unobserved heterogeneous effect. However, we cannot both include a year and firm fixed effects due to the incidental parameter problem.

2.3.5 Main Estimations

In a nutshell, we first utilize the Green Light Program as an explicit instrumental variable to measure the impact of the ENERGY STAR program on innovation, which is our baseline estimation method. Second, we use a predicted value of ENERGY STAR participation as an instrumental variable of the patenting equation. Third, as there is an over-dispersion issue in the count model, we also use a negative binomial model with fixed effects to check the robustness of the models. Last, we also conduct several robustness checks.

2.4 Main Estimation Results

First, we use the IV estimation command (ivpoisson gmm) in STATA[30] to estimate the impact of the instrumental variable on patenting. Several papers also use the GMM estimator to estimate the fixed-effects Poisson model for panel data (Blundell, Griffith, & Windmeijer, 2002; Wooldridge, 1999; Wooldridge, 2010). shows that a participation in the ENERGY STAR Program which is instrumented by the Green Light Program participation positively affects patenting at the 5% significance level.

The surprising results are that none of other variables are significant except debt to asset, a measure of financial risk, in columns (3)-(4). In particular, we expected to see a positive sign in the effect of the number of employees and R&D expenditure. However, it is only statistically significant at the 10% level.

[30] The standard error is already corrected (Windmeijer & Silva, 1997).

Table 3. Patenting equation: Green Light Program as an instrument variable

VARIABLES	(1) No. of Patents	(2) No. of Patents	(3) No. of Patents	(4) No. of Patents
ES_year	1.961**	1.961**	1.961***	1.953***
	(0.952)	(0.953)	(0.469)	(0.466)
ROA	-0.00261	-0.00265	-0.00261	-0.00381
	(0.0408)	(0.0407)	(0.0170)	(0.0171)
DTA	2.423	2.418	2.423**	2.470**
	(2.272)	(2.272)	(1.202)	(1.182)
avgemp3years_ln	0.0969	0.0965	0.0969*	0.101*
	(0.150)	(0.150)	(0.0570)	(0.0577)
avgcapx3years_ln_norm	-0.000476		-0.000476	0.130
	(0.000975)		(0.00214)	(0.127)
Elec_price	-0.000606	-0.000607	-0.000606	-0.000613
	(0.000788)	(0.000789)	(0.00198)	(0.00198)
avgxrd3years_ln_norm		-0.000816		-0.132
		(0.000920)		(0.135)
Constant	-0.446	-0.443	-0.446	-0.478
	(0.620)	(0.620)	(0.436)	(0.431)
Observations	309	309	309	309

Notes:
(1)-(2). Std. Err. adjusted for 8 clusters in industry
(3)-(4). Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Second, we use a predicted value of ENERGY STAR participation as an instrumental variable of the patenting equation. In the participation equation, the within variation of being an ENERGY STAR partner is greater than the between variation[31] of being an ENERGY STAR partner, so the standard error of the fixed effects coefficients is tolerant enough to be used in the patenting equation. To estimate a binary participation decision, a logit model can be consistently estimated with fixed effects and is preferred to a probit model in panel data structure. In the patenting equation, one could use a two-stage estimation method to estimate the effects of ENERGY STAR by including the ENERGY STAR hat from the participation equation.

[31] The between variation of being ENERGY STAR partner is 0.24 which is less than the within variation 0.30.

However, the standard error would be incorrect. As a robustness check, Table 4 shows the result of the patenting equation. Similarly, the key finding is ENERGY STAR partners are more likely to innovate than non-ENERGY STAR partners.

Table 4. Patenting equation: Energy Star hat as an instrument variable

VARIABLES	(1) No. of Patents	(2) lnalpha	(3) No. of Patents	(4) lnalpha	(5) No. of Patents	(6) lnalpha
ES_hat	2.734***					
	(1.037)					
ES_hat2			2.070***			
			(0.652)			
ES_hat3					1.512***	
					(0.314)	
roa	-0.0110		0.00533		-0.0492***	
	(0.0219)		(0.0200)		(0.00814)	
dta	3.289***		3.053**		-3.122	
	(0.823)		(1.300)		(2.911)	
avgemp3years_ln	0.150		0.225		-1.266***	
	(0.121)		(0.171)		(0.169)	
avgcapx3years_ln_norm	-0.000543		-0.107		-1.013***	
	(0.00134)		(0.124)		(0.208)	
elecprice	-0.00185		-0.00213		0.00510***	
	(0.00170)		(0.00267)		(0.00130)	
Constant	-0.560	0.344	-0.318	0.282	8.437***	-1.444***
	(0.429)	(0.336)	(0.954)	(0.289)	(1.004)	(0.214)
YEAR FE	NO		YES		NO	
FIRM FE	NO		NO		YES	
Observations	309	309	187	187	112	112

Notes:
(1), (3), (5). Std. Err. adjusted for 8 clusters in industry
*** p<0.01, ** p<0.05, * p<0.1

2.5 Robustness Checks

As a robustness check, the appendix shows negative binomial estimation results. It shows consistent results while the magnitude of the coefficients is smaller than the instrumental variable approach. For further robustness checks, we replace the three-year moving average of covariates by one-year or two-year lags: the number of employees, the average of capital expenditure, and the average of R&D expenditure. Both cases are consistent with the main model estimation results. Because three of our control variables are highly multicollinearities[34], we remove two of them and check the robustness of our findings. The main findings are robust after including each of them. We also relax the number of five patents' assumptions and found consistent results.

2.6 Further Estimation Results

Table 5 shows an estimation result of an instrument variable Poisson with a country and Energy Star interaction term. This interaction term indicates a differential impact between U.S. and non-U.S. companies in response to the ENERGY STAR criteria update in 1997. We could not find any evidence of a differential impact of domestic or foreign firms on innovation. This could be expected because ENERGY STAR is a flagship voluntary energy efficiency program in the United States, so foreign ENERGY STAR firms have also been affected by the ENERGY STAR criteria update. Therefore, there is no particular reason to believe that U.S. firms are more likely to innovate than non-US firms in response to the policy change.

[34] Refer to the Table 8.

Table 5. A differential impact of domestic and foreign firms

VARIABLES	(1) Poisson IV	(2) Poisson IV	(3) Poisson IV
Inter_ES_US	23.50	35.43	32.39
	(15.53)	(39.16)	(29.73)
ENERGY STAR	-25.58	-41.94	-38.11
	(16.97)	(45.45)	(34.12)
Return on Assets	-0.0323	-0.0295	0.0147
	(0.0464)	(0.0873)	(0.0507)
Debt to Assets	-1.435	-17.31	-15.15
	(3.621)	(19.11)	(14.64)
Log (3-year moving average of number of employees)	0.628		
	(0.558)		
Log (3-year moving average of capital expenditure)	0.167		
	(0.429)		
Log (3-year moving average of R&D expenditure)	-0.656*		
	(0.370)		
Log (One-year lag of average of number of employees)		2.525	
		(1.708)	
Log (One-year lag of capital expenditure)		-3.818	
		(3.233)	
Log (One-year lag of R&D expenditure)		1.602	
		(1.904)	
Log (Two-year lag of average of number of employees)			3.238*
			(1.764)
Log (Two-year lag of capital expenditure)			-3.194
			(2.144)
Log (Two-year lag of R&D expenditure)			0.550
			(0.902)
Constant	0.281	6.751	6.544
	(1.110)	(5.772)	(4.037)
YEAR FE	YES	YES	YES
FIRM FE	YES	YES	YES
Observations	309	282	281

Notes:
1. Exponential mean model with endogenous regressors
2. Robust standard errors in parentheses
3. *** p<0.01, ** p<0.05, * p<0.1

Table 6 shows an estimation result on the interaction term between the mandatory policy change in 2001 and ENERGY STAR partners in order to isolate the differential effect of ENERGY STAR and non-ENERGY STAR firms. When it came to the mandatory policy change, we found no evidence supporting an impact on ENERGY STAR partner firms of the federal refrigerator efficiency standards update in 2001. The standards update in 2001 did not give ENERGY STAR participating companies more incentive to invent energy-efficient technologies. However, the energy efficiency standard update in 2001 gives an incentive to innovate to non-ENERGY STAR firms, which is the main purpose of the mandatory policy.

One possible explanation is the crowding effects between mandatory environmental policy and voluntary environmental policy associated with ENERGY STAR partners. It is plausible that increases in energy patents in response to the voluntary environmental policy led to a lesser incentive to further develop energy-efficient technologies because ENERGY STAR firms already meet the mandatory policy criteria. It is possible that the effectiveness of the voluntary program may crowd out the effectiveness of the mandatory program. It is also due to path-dependent technological development trajectories. So, we expect to see less effect of the interaction terms. More rigorous analysis is needed to verify the relationship.

Table 6. Interaction between ENERGY STAR and Mandatory Policy

VARIABLES	(1) Poisson IV	(2) Poisson IV	(3) Poisson IV
ENERGY STAR*Mandatory	-4.598**	-2.874**	-2.891**
	(1.796)	(1.271)	(1.186)
Mandatory	-0.330	-0.328	-0.455
	(0.408)	(0.452)	(0.455)
ENERGY STAR	5.501***	3.547**	3.399**
	(1.911)	(1.529)	(1.458)
Return on Assets	0.00964	0.00717	0.0116
	(0.0150)	(0.0157)	(0.0166)
Debt to Assets	3.275**	2.932	2.301
	(1.609)	(2.356)	(2.393)
Log (3-year moving average of number of employees)	-0.138		
	(0.179)		
Log (3-year moving average of capital expenditure)	0.196		
	(0.164)		
Log (3-year moving average of R&D expenditure)	0.142		
	(0.192)		
Log (One-year lag of average of number of employees)		0.0719	
		(0.264)	
Log (One-year lag of capital expenditure)		-0.174	
		(0.388)	
Log (One-year lag of R&D expenditure)		0.255	
		(0.261)	
Log (Two-year lag of average of number of employees)			0.346
			(0.283)
Log (Two-year lag of capital expenditure)			-0.273
			(0.372)
Log (Two-year lag of R&D expenditure)			0.120
			(0.235)
YEAR FE	YES	YES	YES
FIRM FE	YES	YES	YES
Constant	-0.288	-0.0851	0.549
	(0.441)	(0.923)	(0.902)
Observations	309	282	281

Notes:
1. Exponential mean model with endogenous regressors
2. Robust standard errors in parentheses
3. *** p<0.01, ** p<0.05, * p<0.1

2.7 Conclusions

This paper contributes to an understanding of whether voluntary environmental policy in general—and ENERGY STAR in particular—spurs or detracts from firms' environmental innovation. We found a result suggestive of the impact of ENERGY STAR on household appliance firm's innovation. It shows that ENERGY STAR firms more actively participated in energy-related household appliance patents in response to the ENERGY STAR criteria update in 1997. The results show strong evidence that an ENERGY STAR criteria change can spur innovation in household appliance firms that participate in ENERGY STAR. There is no differential impact between U.S. firms and non-U.S. firms. It also shows the potential evidence of the crowding-out effect on innovation of a mandatory environmental policy and a voluntary environmental policy.

From the firms' collective viewpoint, they will incur up-front costs to improve the energy efficiency of their products and thus lose short-term profits. A new energy-efficient technology could be worth billions of dollars, but companies must bear a considerable amount of upfront costs that may lead to uncertain discounted future benefits. Due to the nature of energy efficiency investments, firms are reluctant to invest in R&D to improve energy-efficient technologies. Additionally, firms' decisions depend on their "discount rate." As a result, energy-efficient technologies will be underfunded. Therefore, government interventions play a significant role in guaranteeing a steady supply of energy-efficient technologies in the market. According to Porter (1991), environmental regulation can be an incentive for technological innovation. If environmental regulations are properly designed, they not only result in improved environmental performance but also partially offset the costs of regulation. The rationale behind this mechanism is that a regulation can be an incentive for innovation and create progress a firm's technical solutions.

The identification of energy-related household appliance patents in this paper was broader than Taylor, Fujita, Dale, and McMahon's (2012) list of patents, which was very conservative. We suggest that Taylor et al.'s (2012) identified patents (64 patents between 1976 and 2011) were the lower bound, and this study's identified energy-related refrigerator patents (2,530 patents between 1985 and 2004) are the upper bound. So, we suggest that it would be more accurate to identify energy-related household appliance patents including emerging technologies at the patent office rather than ex-post methodology.[36]

Similarly with Graham, Brouhle, and Ramirez (2014)'s paper, it would be necessary to conduct patent weighted citation analysis in order to measure information flow from the ENERGY STAR participants to non-participants. Previous literature such as Delmas and Keller (2005) argues for a free-ride effect from voluntary environmental policy participants to non-participants. Building on the Jaffe, Trajtenberg, and Henderson (1993)'s seminal paper, this is an area of future research.

Another remaining question is whether technological innovation spurs a tightening of the mandatory energy efficiency policy from 2001. It is plausible that firms participating in ENERGY STAR are already satisfying the minimum energy efficiency requirement of the mandatory policy in 2001 so that ENERGY STAR firms may lobby to the government to strengthen the minimum criteria. ENERGY STAR firms want to further enjoy the first mover advantage. Compared to non-ENERGY STAR firms, future work is required to test a reverse causality between voluntary and mandatory environmental policy and technological innovation.

[36] The most comprehensive approach thus far was done from the European Patent Office (EPO).

Table 7. A list of firm names (Participants vs. Non-participants)

Company Name	ES Partner	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
501 HITACHI LTD	1	5	1	1	1	2	1	2	1	2	3	2	4	8	3
AB ELECTROLUX	1	4	1	3	2	1	1	1	1	2	1	0	1	1	0
AMANA REFRIGERATION INC	1	1	2	1	1	0	0	0	0	0	0	0	0	0	0
ECOLAB	1	0	1	0	0	0	0	1	0	1	0	1	0	0	1
FISHER & PAYKEL APPLIANCES LTD	1	0	0	0	0	0	0	0	3	1	0	5	1	0	0
GEN ELECTRIC CO	1	4	7	17	8	11	8	7	8	2	2	16	25	5	12
MAYTAG CO	1	3	4	3	6	3	5	4	10	10	5	6	12	29	30
SAMSUNG ELECTRONICS CO LTD	1	0	0	0	12	13	17	19	27	25	13	5	8	14	21
UNITED TECHNOLOGIES CORP	1	0	0	0	0	1	0	0	1	1	0	3	0	3	8
WHIRLPOOL CORP	1	14	8	4	20	5	7	7	14	5	9	8	12	14	16
501 HONDA GIKEN KOGYO KK	0	0	0	0	0	0	0	0	2	2	1	0	1	0	1
501 KK TOSHIBA	0	6	5	4	4	5	2	2	0	2	6	3	5	3	1
501 SHARP KK	0	0	0	0	0	0	0	0	0	0	0	0	5	1	0
ATSUSHITA ELECTRIC IND CO LTD	0	1	2	1	2	0	1	1	0	0	0	1	4	2	4
BASE CORP	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
BOSCH & SIEMENS HAUSGERAETE GMBH	0	0	0	0	0	0	0	1	6	0	1	0	5	6	6
CHUBU ELECTRIC CO INC	0	0	0	0	5	3	3	1	1	2	4	3	5	2	0
CHURCH & DWIGHT	0	0	3	2	0	1	0	0	0	0	0	0	0	0	0
COCA COLA BOTTLING WORKS CO	0	0	0	0	0	0	0	0	0	1	2	3	6	0	0
COGATE PALMOLIVE CO	0	6	18	1	6	6	1	1	0	3	6	2	4	2	4
ELTEK SPA	0	0	0	0	0	0	0	0	0	0	0	2	3	1	0
HAC	0	0	4	0	1	2	1	0	0	0	0	0	0	0	0
HELIX TECH	0	1	0	0	0	0	0	2	1	1	0	0	1	1	1
ILEVER HOME & PERSONAL CARE USA	0	0	0	0	0	0	0	0	0	0	0	6	4	3	0
INTEE CORP	0	0	0	0	0	0	0	0	0	0	0	2	1	1	2
ISTEON GLOBAL TECH INC	0	0	0	0	0	0	0	0	0	0	0	0	1	3	2
PROCTER & GAMBLE CO	0	2	1	3	5	2	12	19	12	4	9	12	17	9	8
RACKITT BENCKISER NV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SANGO ELECTRIC CO LTD	0	1	3	2	1	2	0	1	6	0	2	1	1	10	3

Table 8. Number of Patents by Assignee Country

Year	DE	IT	JP	KR	NL	NZ	SE	US	Sum
1990	0	0	13	0	0	0	4	31	48
1991	0	0	11	0	0	0	1	48	60
1992	0	0	8	0	0	0	3	31	42
1993	0	0	13	12	0	0	2	47	74
1994	0	0	12	13	0	0	1	31	57
1995	0	0	7	17	0	0	1	34	59
1996	1	0	7	19	0	0	1	41	69
1997	6	0	10	27	0	3	1	46	93
1998	0	0	8	25	0	1	2	28	64
1999	1	0	16	13	0	0	1	33	64
2000	0	2	10	5	6	5	0	53	81
2001	6	3	25	8	4	1	1	79	127
2002	6	1	26	14	3	0	1	67	118
2003	6	0	12	21	0	0	0	84	123
Sum	26	6	178	174	13	10	19	653	1079

*DE(Germany), IT(Italy), JP(Japan), KR(South Korea), NL(Netherlands), NZ(New Zealand), SE(Sweden), US(United States)

Table 9. Correlation Matrix

	Green Light	ROA	DTA	Avg. employee_3year	Avg. capx_3year	Avg. exp_3year
Green Light	1					
ROA	-0.0047	1				
DTA	0.0528	-0.302	1			
Avg. employee_3year	0.1388	-0.326	0.22	1		
Avg. capx_3year	0.1291	-0.201	0.1457	0.8457	1	
Avg. exp_3year	0.0121	-0.27	0.0662	0.8613	0.9116	1

Table 10. Summary Statistics (Participants vs. Non-participants)

Variable	ENERGY STAR			Non-ENERGY STAR		
Dependent variables	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
ES_year	128	0.46875	0.501	217	0	0
No. of patents(by year and firm)	128	5.242188	6.7658	217	1.880184	3.058749
Independent variables						
greenlight	128	0.46875	0.501	217	0.110599	0.31436
ROA-Return on Assets=net income/total assets	126	3.83283	5.2818	217	5.931655	7.810504
DTA-debt to assets	126	0.1773631	0.0808	217	0.14158	0.095713
employee: three-year moving average	115	4.255179	1.3553	194	3.860609	2.042636
Capital expenditure: log of the average of a firm's past three years capital expenditure	122	6.211176	1.8518	198	6.060389	2.525626
R&D expenditure: log of the average of a firm's past three years expenditure	115	5.442749	1.832	197	5.780289	2.546647
Beverage and Tobacco Product Manufacturing	128	0	0	217	0.064516	0.246238
Chemical Manufacturing	128	0.109375	0.3133	217	0.304148	0.461109
Machinery Manufacturing	128	0	0	217	0.129032	0.336011
Computer and Electronic Product Manufacturing	128	0.3046875	0.4621	217	0.170507	0.376947
Electrical Equipment, Appliance, and Component Manufacturing	128	0.328125	0.4714	217	0.129032	0.336011
Transportation Equipment Manufacturing	128	0.109375	0.3133	217	0.156682	0.364341
Miscellaneous Manufacturing	128	0.0390625	0.1945	217	0	0
Others	128	0.109375	0.3133	217	0.046083	0.21015
Germany	128	0	0	217	0.073733	0.26194
Italy	128	0	0	217	0.041475	0.199846
Japan	128	0.109375	0.3133	217	0.322581	0.468545
South Korea	128	0.0859375	0.2814	217	0	0
United Kingdom	128	0	0	217	0.082949	0.276443
New Zealand	128	0.0390625	0.1945	217	0	0
Switzerland	128	0.109375	0.3133	217	0	0
United States	128	0.65625	0.4768	217	0.479263	0.500725

Table 11. ENERGY STAR participating firms

Name	Year of participation	Sources
SAMSUNG ELECTRONICS CO LTD	1996	http://news.samsung.com/us/2015/04/06/samsung-electronics-wins-two-2015-energy-star-partner-of-the-year-awards-for-sustained-excellence-and-climate-communications/
CARRIER CORORATION	1997	http://dms.hvacpartners.com/docs/1009/Public/02/58MXA-11PD.pdf
GEN ELECTRIC CO	1997	https://www.energystar.gov/ia/partners/prod_development/revisions/downloads/clotheswash/GE_CW_Comments4.15.05.pdf?5442-a1e8
MAYTAG CO	1997	https://www.energystar.gov/ia/partners/prod_development/revisions/downloads/clotheswash/Maytag.pdf?5442-a1e8
AB ELECTROLUX	1998	http://ieeexplore.ieee.org/document/645988/
AMANA REFRIGERATION INC	1998	https://www.whirlpool.com/digitalassets/MLPDF/Use%20and%20Care%20Guide%20-%2020070003.pdf
DAEWOO ELECTRONICS CO LTD	1998	http://heinonline.org/HOL/LandingPage?handle=hein.journals/lwpra24&div=42&id=&page=
ELECTROLUX HOME PROD INC	1998	http://ieeexplore.ieee.org/document/645988/
WHIRLPOOL CORP	1998	https://www.energystar.gov/index.cfm?fuseaction=pt_awards.showAwardDetails&esa_id=384
WHIRLPOOL EURO BV	1998	https://www.energystar.gov/index.cfm?fuseaction=pt_awards.showAwardDetails&esa_id=384
WHIRLPOOL INT BV	1998	https://www.energystar.gov/index.cfm?fuseaction=pt_awards.showAwardDetails&esa_id=384
501 HITACHI LTD	1999	http://tv.manualsonline.com/manuals/mfg/hitachi/42hdt79_55hdt79_42hdx99_55hdx99_1_2.html
ECOLAB	1999	ftp://ftp.cs.huji.ac.il/cs/adir/mirror/LDP/HOWTO/pdf/Ecology-HOWTO.pdf
FISHER & PAYKEL APPLIANCES LTD	1999	http://link.springer.com/chapter/10.1007/978-3-642-60020-3_14#page-1
BOSCH & SIEMENS HAUSGERAETE GMBH	2007	http://www.bosch-home.com/us/press-releases-detail.html?pressrelease=epa-recognizes-bosch-home-appliances-with-2014-energy-star%C2%AE-partner-of-the-year-sustained-excellence-award~13147

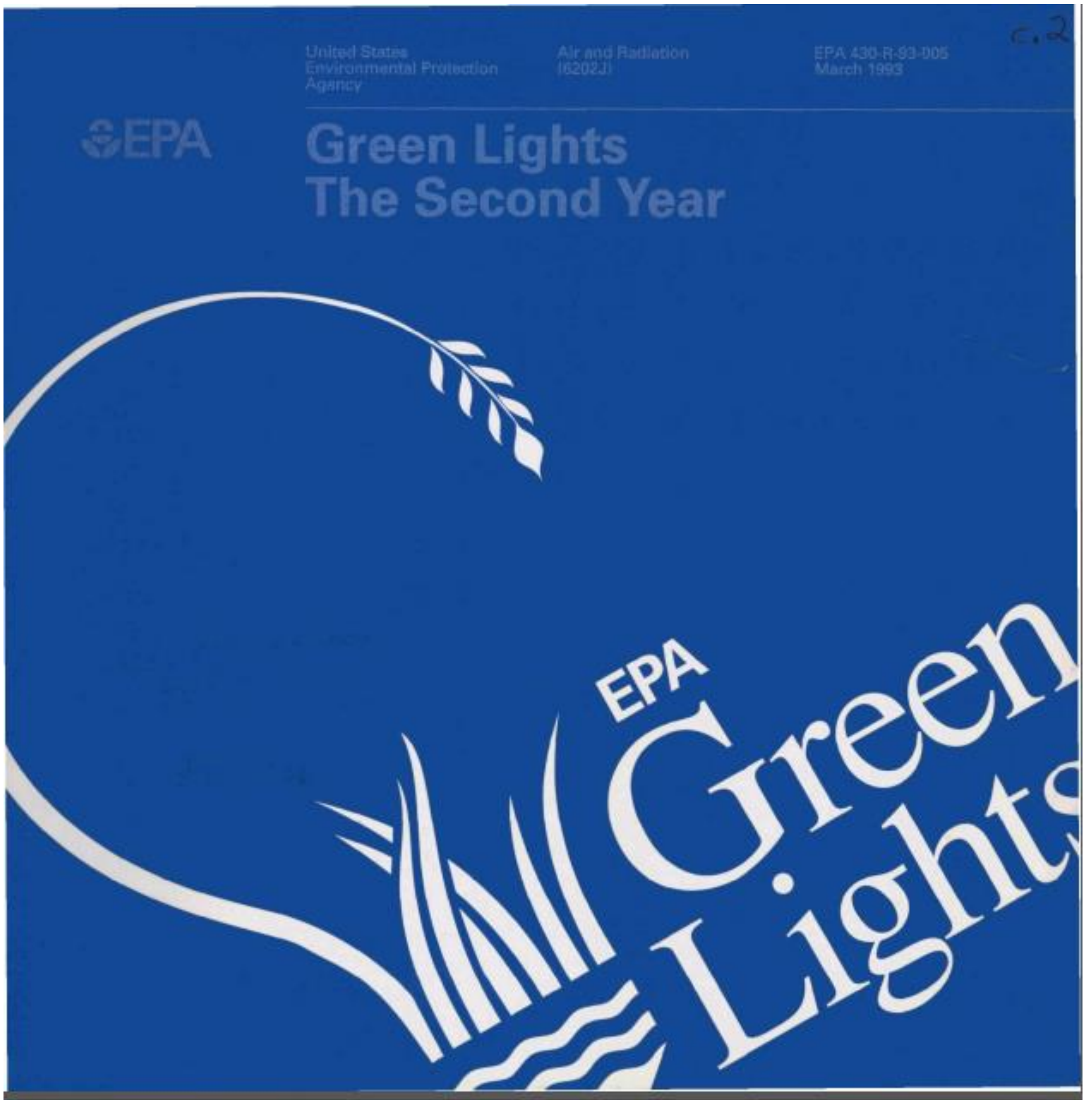

Figure 4. A sample of Green Lights Report

CHAPTER 3. IMPACT OF ENERGY-EFFICIENCY POLICIES ON INNOVATION: THE CASE OF LIGHTING TECHNOLOGIES

3.1 Introduction

Lighting accounts for more than 20% of the total electricity consumed in the U.S. (Navigant Consulting, 2002; Azevedo, Morgan, & Morgan, 2009). According to the International Energy Agency (IEA)'s report, the potential amount of electricity saved in building lighting by 2030 would be equivalent with the entire electricity consumed in Africa in 2013.[37] Among different types of lighting technologies, fluorescent lamps account for 42% of lighting electricity, 26% for high-intensity discharge lamps, and 22% for incandescent lamps (Navigant Consulting, 2012). Lighting sources in this chapter were categoraized into three broad categoeis: incandescant, compact fluorescent lamps (CFLs), and light-emitting diodes (LEDs).

Reflecting on the history of technological development in lighting, light bulb technologies have continuously developed to serve consumer needs better.[39] An incandescent light bulb is a device that emits light when an electric current passes through a filament until it glows (Zhu & Humphreys, 2012). The invention of the first incandescent light bulb by Thomas Edison and other precursors was the foundation upon which subsequent incandescent light bulb designs were based (Friedel & Israel, 2010). It has served as the single most popular lighting technology for more than 100 years. For example, the story of the firehouse light bulb that was installed in 1903 is interesting because it is still illuminating in 2015. The price of incandescent

[37] https://www.iea.org/statistics/relateddatabases/worldenergystatisticsandbalances/
[39] https://energy.gov/articles/history-light-bulb

light bulbs has dropped gradually, and the performance of the light bulbs has improved, but it is the least energy efficient of the available technologies. However, incandescent light bulbs were widely used historically due to their comparative price advantage over the two emerging technologies.

Unlike an incandescent light bulb, CFLs generate invisible light that excites a fluorescent coating inside the tube and then emits visible light when the electric current runs through a tube containing argon and mercury vapor (Azevedo et al., 2009). The original fluorescent lamp technology was developed in the late 1940s. A CFL looks like an incandescent light bulb, but it is more energy efficient and last ten times longer. Although it is a bit more expensive, CFLs are cost-effective options in locations where lights are on for long periods of time. U.S. residents were slow to adopt CFLs. Beginning in the late 1980s, utilities engaged in demand-side management to increase consumers' adoption of CFLs, but faced technical difficulties. In the late 1980s and early 1990s, CFLs were bulky and their light performance was not good enough compared to incandescent light bulbs. Therefore, consumers disregarded the innovative technology and tended not to buy expensive CFLs compared to low-cost incandescent light bulbs (Ledbetter, Sandahl, Gilbride, Calwell, & Steward, 2013). Although the market encountered several barriers to the diffusion of CFLs, it seems that consumers are more willing to adopt CFLs than in the past.

In contrast, LEDs are semiconductor devices that produce light; in a light bulb, red, green, and blue LEDs combine to make white light (Zhu & Humphreys, 2012). There are three types of LED lights: solid-state lighting (SSL), organic light-emitting diodes (OLEDs), and light-emitting polymers (LEPs). They emit little heat, which makes them more energy efficient. The first LED was developed in 1961 and it recently emerged as an alternative technology to replace incandescent light bulbs because it has a longer lifespan and is more energy efficient.

CFLs and LEDs are cost-effective to an incandescant lightbulb, but CFLs and LEDs include hazardous materials such as lead, copper, and zinc, while an incandescant lightbulb does not contain them (Lim, Kang, Ogunseitan, & Schoenung, 2013). It seems that CFLs are competing against LED technology due to the rapid price drop of LEDs. The price of CFLs has gradually dropped since 1997, but appears to have recently stabilized. The price of LEDs, on the other hand, has rapidly declined in recent years. Since 2011, the price of LED bulbs has dropped by 28% to 44% per year, depending on lumen output (Gerke, Ngo, Andrea, & Fisseha, 2014).

Several studies also indicate potential energy savings and CO_2 emission reductions when we adopt LEDs. Quirk (2009) indicated that LEDs will significantly improve in the future, but CFLs are already becoming a mature technology. In addition, we can reduce greenhouse gas emissions by adopting more energy-efficient light bulbs. According to a study by the U.S. DOE, if we replace LEDs where it is currently feasible with conventional lightbulbs between 2013 to 2030, we would reduce the electricity for lighting by about 50% in 2030 (Navigant Consulting, 2014).

Table 12 shows the comparison of incandescent light bulbs, CFLs, and LEDs. LED is the most cost-effective option among three technologies. The high upfront cost of LEDs is the main obstacle to high market penetration (National Research Council, 2005; Navigant Consulting, 2006). Even though the upfront cost of LED is the most expensive, the total cost for ten years is the lowest. To increase market penetration, we will continue to make every effort to further reduce the upfront cost of LEDs (Azevedo et al., 2009).

Table 12. Comparison of three lighting technologies

	LED	Compact Fluorescent	Incandescent
Upfront cost	$8	$2	$1
Energy	11 watts	14 watts	60 watts
Efficiency*	0.55	0.2	0.05
Lifetime (hours)	50,000	8,000	1,200
Power @ 6 hours/day	66 Wh/day	84 Wh/day	360 Wh/day
Cost per day @ 11 ₵/kWh	0.72 ₵	0.92 ₵	3.96 ₵
Cost per year @ 11 ₵/kWh	$2.64	$3.37	$14.45
Cost for ten years @ 11 ₵/kWh (discount rate: 7%)	$19.53	$24.86	$106.55

*Source: Author's calculation based on Zhu and Humphreys (2012).

Many researchers have conducted studies to estimate the impact of environmental policy on technological innovation by using patent data (Carrión-Flores & Innes, 2010a; Costantini, Crespi, Orsatti, & Palma, 2015**;** Verdolini & Galeotti, 2011; Noailly & Ryfisch, 2015). They found that there is a positive relationship between environmental policy and technological innovation that is known as the "policy inducement effect" (Brunnermeier & Cohen, 2003; Jaffe & Palmer, 1997; Johnstone, Haščič, & Popp, 2010; Popp, 2002).

Given the discoveries about the generally positive relationship between environmental policy and innovation, what is the role of energy-efficiency policy in technological innovation? There appears to be well-designed energy-efficiency policies that also lead to more inventive activities. However, Sachs (2012) argues that energy-efficiency policies may not be a direct cause of the energy innovation. At first glance, it makes sense because an energy efficiency mandate requires meeting a certain minimum energy efficiency criterion. So, if a firm meets the minimum standards, it does not have any further incentives to engage in innovation. In this paper, we test Sach's conclusions within the empirical context of lighting technologies.

While most of the previous research investigated the impact of domestic policy on domestic technological innovation, Lanjouw and Mody (1996) analyzed the effect of domestic policy on foreign innovation. They found evidence that strict vehicle emission regulations in the United States spurred innovation in Japan and Germany. Subsequently, Popp, Hafner, and Johnstone (2011) found a positive correlation between domestic and foreign regulation and innovation.

Along these lines, we pose the following inquiries: First, what are the major international or domestic lighting policies that spur lighting innovation? Second, what role do these energy-efficiency policies play in inducing CFL and LED patenting? Third, which countries play a crucial role in energy-efficient lighting patenting in response to U.S. policy (i.e., the Energy Policy Act of 2005)?

We study these questions in the empirical context of lighting technological innovation proxy by global patent data. This chapter empirically investigates the causal link between domestic and international energy-efficiency policies on CFL and LED innovation. Internationally, since Japan was the first to begin increasing the energy efficiency of lighting technology, due to the Top Runner Program in 1998 (Grubler & Wilson, 2014), LED innovation was initially more likely to occur among Japanese inventors than other inventors. Domestically, the Energy Policy Act of 2005 has been the most important piece of legislation related to energy-efficient lighting.[40]

[40] The Energy Policy Act of 1992 did not address lighting.

In order to measure the impact of energy-efficiency policy on technological innovation, there are several challenges. First, patent data is not a perfect measure of technological innovation. However, Griliches (1990) argues that patent data is a good proxy variable for innovative activity. Additionally, patent data are the most frequently used metrics to measure a creation of new knowledge (Schmookler, 1962; Griliches, 1990; and Hall, Jaffe, & Trajtenberg, 2001; Schmookler, 1966; Scherer, 1965). There is still controversy regarding whether a patent is a good measure of innovation output. However, patent count at the firm, industry, and country levels can be a useful measure of innovative output in energy technology.[41] Second, energy-efficient technological improvements could be a small portion of inventive activities, so it is highly likely that we cannot find any statistically significant results. However, this is not a major concern in LED and CFL patents. On the contrary, the number of incandescent light bulb patents[42] (104) has been very small since 1976. So we omitted the incandescent light bulb from the analysis.

To provide background of which countries and firms are active in LED patenting, we can identify top 9 LED firms based on the total revenue[43]: Nichia (Japan), Osram(Germany), Samsung Electronics (Korea), Seoul Semiconductor (Korea), Cree (United States), LG Innotek (Korea), Everlight Electronics (Taiwan), Toyoda Gosei(Japan), and Stanley Electric(Japan). These firms could dominate the lighting patenting. Or it could be lighting innovation occurs from

[41] A discussion of the relationship between patent data and energy innovation output is well documented in Popp's (2005) paper.
[42] The IPC code for incandescent light bulb is “F21H.”
[43] https://diarraeg.wordpress.com/2014/10/08/nobel-prize-a-morale-booster-for-japanese-electronics/

small or specialized firms such as Sorra, a start-up LED company, supported by ARPA-E from June 2012 to April 2015 about $6 million.[44]

This chapter is organized as follows. First, since these two policies (1998 and 2005) have become an important route to lighting innovation, we identify policy inducement effects in a difference-in-difference estimation method on CFL and LED innovation, respectively. Second, we explore the differential domestic policy impact on lighting innovation. Third, we identify the effect of the domestic policy uncertainty on lighting innovation which plays a crucial role in providing momentum for energy innovation (Gallagher et al., 2012).

3.2 Background

Table 1 provides international and domestic policies that may affect lighting innovation. Japan initiated the Top Runner Program in 1998 to improve the energy efficiency of end-use products. Unlike the previous mandatory energy efficiency programs in Japan, the Top Runner program was created in response to the Kyoto Protocol[45], which was adopted in Japan on December 11, 1997, to achieve greenhouse gas emissions targets (i.e., a 6% reduction by 2008–2012 in comparison to the 1990 baseline level). In the case of fluorescent lighting technology, the efficiency standard was set to the most efficient product in the market. Therefore, the targets were just achieved right after the implementation of the policy, so it is challenging to measure a rate of technological efficiency improvement (Grubler & Wilson, 2014). However, note that this does not necessarily imply that there were no inventive activities at all. The Light for the 21st

[44] http://www.arpa-e.energy.gov/?q=slick-sheet-project/ammonothermal-growth-gan-substrates-leds
[45] http://unfccc.int/kyoto_protocol/items/2830.php

Century Project in Japan began in 1998 and spurred the innovation of the high-efficient ultraviolet (UV) light-emitting diodes (LED) and phosphor systems.

In the United States, the most significant legislation on energy policy since the Energy Policy Act of 1992 is the Energy Policy Act of 2005. Key pieces of the legislation were a manufacturer and consumer tax incentives and minimum energy-efficiency standards for 16 products. The Energy Policy Act of 2005[46] provided a tax deduction for energy-efficient commercial buildings beginning in 2006. Inventors have incentives to produce more energy-efficient products to meet the requirements. The Energy Policy Act of 2005 set new minimum efficiency standards for several products, which includes the provision of tax incentives to manufacturers. From firms' perspective, this policy appears to spur innovation. Companies have stepped up by taking the initiative to develop more energy-efficient lighting technology. At the same time, the demand for more energy-efficient light bulbs has been rising because of the sharp decline of LED prices. This demand increase would spur innovation among firms as well. Since LEDs are more energy-efficient products than CFLs, we expect to see more innovation in LEDs than CFLs. The Energy Policy Act of 2005 had been discussed since 2001 and was signed into law in August 2005 (Nadel, Prindle, & Brooks, 2006). Since there is a gap between the initial policy discussion and the actual implementation date, high levels of policy uncertainty between 2001 and 2005 could have either hindered or spurred innovation.

Similarly, South Korea replaced 40 W fluorescent lamps with 32 W fluorescent lamps in 2004. Afterward, Korea started its LED Lighting 15/30 Dissemination Project in 2006. In 2008, Korea decided to phase out incandescent light bulbs from the market. It appears that Korea is

[46] http://energy.gov/savings/energy-efficient-commercial-buildings-tax-deduction

also a leader in energy-efficient lighting technologies and has incentives to increase inventive activities in response to the policy change. The EUs' policy related to the direct support of SSL such as EU eco-design Regulation 244/2009 is somewhat belated in comparison to the first-mover countries: Japan, Korea, and the United States. So, the European Lamp Companies Federation called for better policies supporting SSL (European Lamp Companies Federation, 2011).

Several factors affect energy innovation. First, the "Induced Innovation" hypothesis argues that changes in the relative prices of the factors of production can spur innovation within the industry (Hicks, 1932).[47] To control for the impact of energy prices on innovation, we include the electricity price in regression models. Second, technological change can be induced by policy intervention (Jaffe, Newell, & Stavins, 2003), thereby creating a demand for clean technologies. This demand will create incentives for environmental innovation. In order to control for that, we include the growth of household electricity consumption in the econometric model to control for electricity market size (Johnstone et al., 2010). It emphasized the interaction between environmental policy and technology, which can be used as a criterion for policy evaluation. This issue is considered in a growing body of literature (see, for example, Carrión-Flores and Innes, 2010b; Dechezleprêtre, Neumayer, & Perkins, 2015; Lanjouw and Mody, 1996; Popp, 2006b; Verdolini & Galeotti, 2011).

Dechezleprêtre and Glachant (2014) raised a question about whether foreign environmental policy influences domestic innovation. Dechezleprêtre et al. (2015) analyzed the

[47] For an empirical analysis, Newell, Jaffe, and Stavins (1999) developed a methodology for testing the hypothesis by estimating a product characteristic of household appliances.

cross-border diffusion of new technologies. Lanjouw and Mody (1996) analyzed the effect of policy on innovation in other countries. They found the evidence that strict vehicle emission regulation in the U.S. spurred the innovation in Japan and Germany. However, this study is not based on the econometric model to provide sufficient evidence to support the causality. Popp (2006b) found that strengthening U.S. standards led to more patenting in the U.S., not internationally. Subsequently, Popp, Hafner, and Johnstone (2011) also found the positive correlation between domestic and foreign regulation and innovation.

Figure 5 shows LED patent applications per year. Japanese inventors are the leaders in this arena, followed by Korean and the United States inventors, respectively. It seems there was a sudden increase in the number of LED patent applications in 1998. It implies that an unknown exogenous factor affected this uptake, which we argue is due to the Top Runner Program.

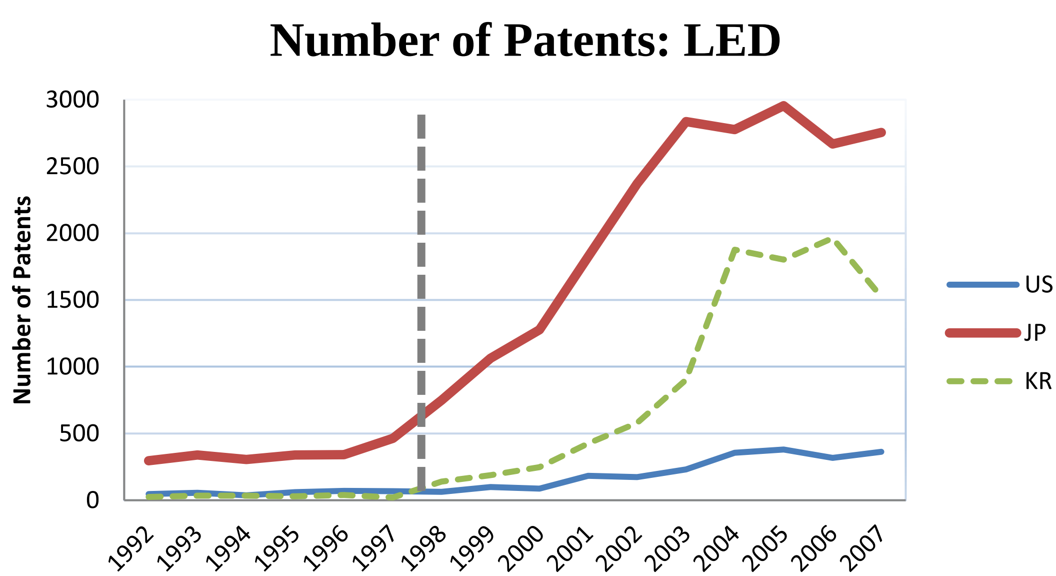

Figure 5. LED Patent applications per year (1992-2007)

Figure 6 shows a clear picture. It is visually evident that there is a discontinuity in 1998. This graph is consistent with an impact of the Top Runner Program on lighting patenting. Therefore, we hypothesize the following.

***Hypothesis 1.1*: Domestic energy-efficiency policy positively influences domestic lighting patenting.**

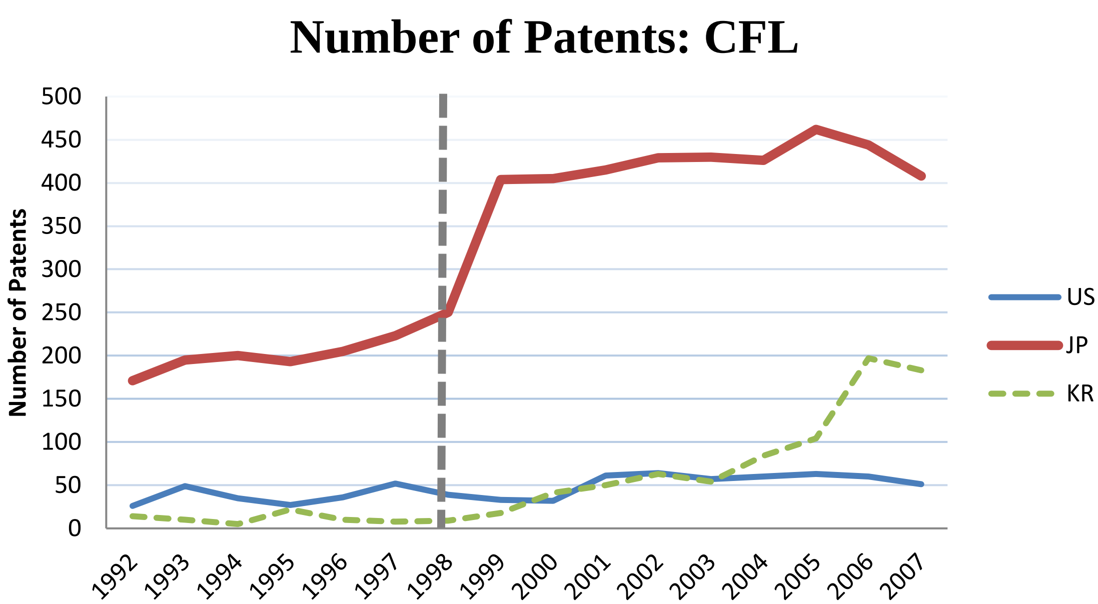

Figure 6. CFL Patent applications per year (1992-2007)

Since we cannot clearly see the United States' patenting behavior, due to the Y-axis scaling issue, we draw it separately in Figure 7 and Figure 8. Figure 7 shows that there is an increasing pattern after 2001 in LED patenting. On the other hand, there are two regimes in CFL patenting: 1992-2001, and 2001–2007. It suggests an exogenous shock may affect lighting patenting. In this case, the Top Runner Program may positively affect the United States patenting. Therefore, we hypothesize the following.

***Hypothesis 1.2*: Domestic energy-efficiency policy positively influences foreign lighting patenting.**

The effect of policy uncertainty on innovation is understudied, and it is hard to find a lot of empirical studies to support the hypothesis that policy uncertainty plays as significant a role as the policy stringency (Johnstone, 2011), but there is anecdotal evidence to support the argument. Recently, Löfgren, Millock, and Nauges (2008) found the role of policy uncertainty on abatement investment decisions. Barradale (2009) also argued the importance of policy predictability in the renewable energy domain.

Recently, several scholars emphasized this relationship (Bhattacharya, Hsu, Tian, & Xu, 2013). Kalamova, Johnstone, and Hascic (2012) categorized this relationship into four types of policy uncertainty: uncertainty regarding the stringency of the policy, uncertainty relating to the timing of the introduction of the policy, uncertainty relating to the nature of the policy instrument and uncertainty relating to the durability of the policy. An unexpected and frequent change in environmental policy can discourage firms from investing in innovation. Firms under regulatory uncertainty may not precisely calculate the costs and benefits of environmental improvement (Considine & Larson, 2006). Under uncertain policy conditions, firms are less likely to invest in R&D, which results in less output (Bosetti & Victor, 2011; Nemet, 2010; Gallagher, Grübler, Kuhl, Nemet, & Wilson, 2012). In energy technology innovation literature, several scholars also underscored that impotance of policy stability (Grubler & Wilson, 2014). Most of case studies in their book support that policy credibility and continuity is one of key factors for successufl energy technology innovation system.

In this chapter, the Energy Policy Act of 2005 was initially discussed in 2001 and was almost finalized in 2003. It took approximately four years to implement the act. Foreign inventors had incentives to file patent applications to preempt lighting innovation. Considering the size of the U.S. market, it is plausible foreign inventors filed patent applications to protect their intellectual property with the U.S. Patent and Trademark Office (USPTO) and other major patent offices at the same time, even before the Energy Policy Act of 2005 was implemented. Even if U.S. government policy is uncertain, foreign inventors have incentive to protect their intellectual property rights for various reasons such as licensing or selling the invention, good image for company's market value. On the other hand, domestic inventors are reluctant to invest their R&D until the actual implementation of the policy, so domestic inventors are less likely to respond to policy uncertainty. Or we even expect to see a negative relationship between domestic policy uncertainty and domestic lighting patenting. In a nutshell, we dichotomize the impact of domestic policy uncertainty on domestic and foreign lighting patenting. Therefore, we hypothesize the followings:

***Hypothesis 2.1*: Domestic policy uncertainty negatively affects domestic lighting patenting.**

***Hypothesis 2.2*: Domestic policy uncertainty positively affects foreign lighting patenting.**

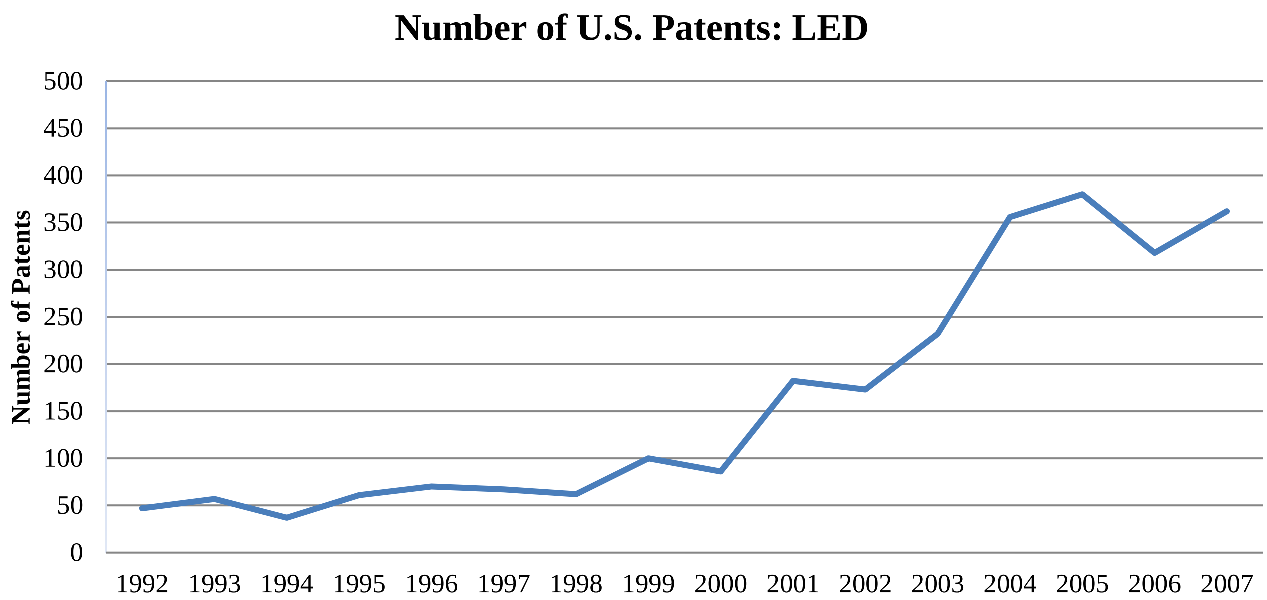

Figure 7. LED patent applications

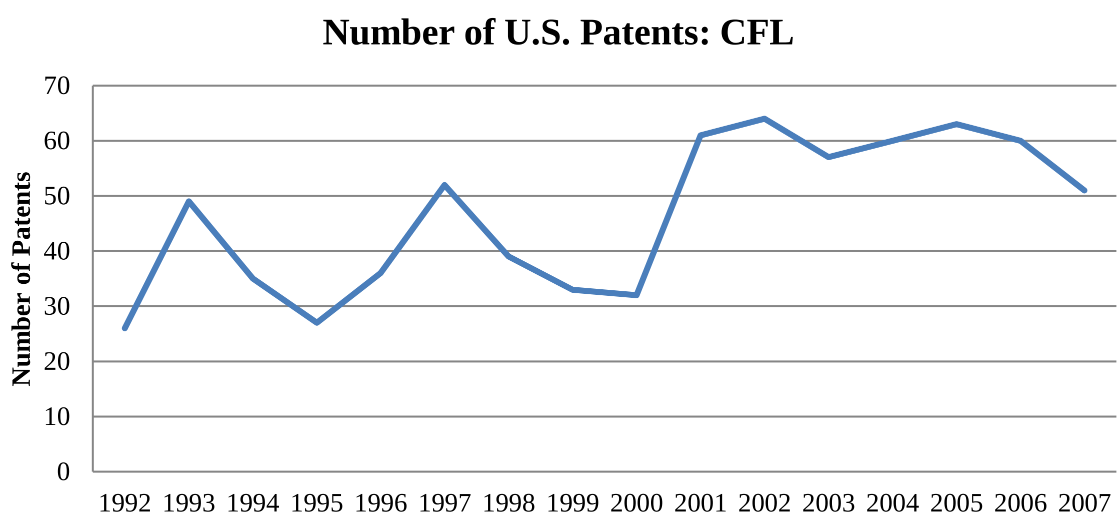

Figure 8. CFL patent applications

3.3 Methods

3.3.1 Construction of data

We collected patent data from the EPO/OECD World Patent Statistical Database (PATSTAT)[50] to analyze inventive behaviors related to LEDs and CFLs across countries. PATSTAT contains patents filed in more than eighty patent offices and includes more than sixty-five million patent applications and thirty million granted patents. However, PATSTAT has a significant missing inventor/applicant-country information problem, especially for Japanese patents. To overcome this challenge, we filled in the missing country information from two patent families (i.e., simple [DOCDB] and extended [INPADOC]), as well as the individuals' names and identification. For the rest, we use the common first name to fill in the missing country information. After that, we drop the remaining missing values (fewer than 5% of the total patents). In order to better count the number of patents by country, we use the fractional count. This method improves the international comparability of patent counts (Hélène Dernis & Guellec, 2001). Alternatively, we also check the robustness of our findings by counting first country of inventors. Our findings are robust to different ways of defining the dependent variable.

In order to retrieve relevant patents, we rely on two definitions of lighting technologies. First, the OECD and EPO (OECD, 2012) identified "technologies related to climate change mitigation and adaptation." This category includes lighting technologies that map into the international patent classification (IPC) codes. For example, it identifies LEDs as "H05B" or "F21K"[51] and CFLs as "H01J 61." Dechezleprêtre, Martin, and Mohnen (2013) used the same IPCs to discern between clean and dirty technologies. Since these IPCs do not capture the recent

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[50] PATSTAT Oct 2013 edition. PATSTAT data comes from the Enterprise Innovation Institute at Georgia Institute of Technology.

[51] H05B33: Electroluminescent light sources (LED), F21K9: Electric lamps using semiconductor devices as a light-generating element, for example by using light emitting diodes (LED)

development of OLED technologies, we also add additional IPCs related to LEDs (Simons & Sanderson, 2011; Sanderson & Simons, 2014). Table 19 provides the description of IPCs related to lighting technologies.

To show different angles of the constructed data, we restrict Japanese patent applications filed in the JPO and compare them in the USPTO, which are shown in Figure 12 and Figure 13. Figure 13 shows that Japanese inventors had filed LED patent applications since the late 1990s. On the other hand, the number of patent applications in the USPTO started to increase around 2003, shown in Figure 12. These Figures show a clear difference between the JPO and USPTO patent applications related to lighting technologies. The most notable difference is that Japanese inventors started to file patent applications to the JPO around 1998 and then filed patent applications to the USPTO around 2001. The possible explanation is that Japanese inventors have incentives to file patent applications to the USPTO, which protects their property rights in the potential significant energy-efficient lighting market in response to the Energy Policy Act of 2005.

3.3.2 Difference-in-difference

Table 20 reports the number of patents by country of the inventors between 1992 and 2007 for both LEDs and CFLs. Japan is the leading country in patenting, followed by Korea, the United States, and Germany. We assess the number of patents by fractional country counts by the extended patent family.[60] Figure 11 provides the description of the number of patents filed in

[60] We detect a structural break in 2006 with the full sample (1966–2013) and trimmed sample (1974–2006). We also conduct a structural break test with the full sample (1980–2010) and trimmed sample (1986–2006) and find the same result.

three patent offices, the USPTO, JPO, and EPO, and shows the significant patenting surge by Japanese inventors. The triadic patent count eliminates home-advantage bias and represents patents of high value. In order to better represent the inventors' country information; we relied on a fractional country count as opposed to the first-inventor country information.

This chapter follows economics of energy innovation literature and the relationship between R&D funding, electricity consumption, and energy prices, economic growth and technological innovation is expressed controlling for following variables[61]: energy efficient Research, Development and Demonstration (RD&D) expenditure, the growth of household electricity consumption, electricity price[62], and the growth of GDP. To be more specific, RD&D expenditure[63] for nineteen countries[64] is included in IEA's energy technology research and development database.[65] The growth of household electricity consumption data[66] come from IEA's Energy Balances Database.[67] Electricity price data[68] come from residential end-user prices, which can be obtained from IEA's Energy Prices and Taxes Database. We eliminated duplicates and restricted data to the span of time between 1992 and 2007. The growth of GDP data comes from the Organization for Economic Co-operation and Development (OECD) database.[69] It is expected that the signs of RD&D expenditure and electricity price are positive.

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[61] We restrict to the nineteen countries in order to match control variables.
[62] USD PPP/unit
[63] Total RD&D in Million USD (2013 prices and PPP) of the energy efficiency. RD&D covers basic research, applied research, experimental development, and demonstration of a prototype of a technology. https://www.iea.org/media/statistics/questionnaires/RDDQuestionnaire.pdf
[64] Nineteen countries are: Japan, United States, Canada, Korea, Germany, United Kingdom, Netherlands, Switzerland, France, Sweden, Norway, Italy, Finland, Australia, Austria, Belgium, Denmark, Spain, and New Zealand
[65] http://wds.iea.org/WDS/ReportFolders/ReportFolders.aspx
[66] The growth rate is calculated by (Post consumption/current consumption)^(1/9)-1
[67] http://www.iea.org/statistics/topics/energybalances/
[68] The missing data are interpolated.
[69] https://stats.oecd.org/index.aspx?queryid=60702#

To measure the impact of the energy efficiency policy on innovation, it is neither possible to run a randomized experiment nor to find a good instrument variable. Instead, a difference-in-difference estimation method allows us to estimate the net effect of policy change: the total number of patent application changes minus the the number of patent applications that would have been filed anyway. So, this method compares the number of patent applications for a treatment country of inventors directly affected by the policy change with those for a control group of similar inventors. It was first used in estimating the minimum wage impact on employment in 1992 (Card & Krueger, 1994). Because this method is not assumption free, we also checked the common trend assumption, which is shown in Figure 5 through Figure 8.

We identify the impact of domestic policy on the domestic lighting patenting in the case of Japan. First, we identify the effect of the Top Runner Program of the Energy Conservation law (1998) on the number of patent applications. Second, we identify the effect of the Energy Policy Act of 2005 on lighting patenting. A standard difference-in-difference regression model to compare before and after the policy change is specified as:

$$No.Patents_{i,t} = \beta_1 + \beta_2 Country_{i,t} + \beta_3 POST_t + \beta_4 Country_{i,t} \times POST_t + \beta X_{i,t} + \alpha_t + \gamma_i + \varepsilon_{\mathrm{i,t}} \tag{5}$$

Where i=1,…..,19 refers to the country and t=1992,…,2007 refers to time. The **Country** is the inventor country. **POST** indicates the period after the policy implementation. This variable is a dummy variable which coded “1” after the policy implementation, and “0” otherwise. **X** are control variables: **RD&D** refers to energy efficiency RD&D expenditure. **ELEC** refers to the growth of household electric consumption. **PRICE_ELEC** refers to the household electricity price data. **GDP** refers to the growth of Gross Domestic Product. $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ each refer to time and country fixed effects. In addition, all the remaining errors are captured in the $\boldsymbol{\varepsilon}$.

3.3.3 Estimation Results

Table 13 shows that **POST×JP** is statistically significantly positive in both technologies. Note that the magnitude of the LED coefficient is far greater than the coefficient of CFL (about ten times greater). The plausible explanation is that LED patenting is mainly driven by the combination of two Japanese policies: the 21st Century Lighting Project and the Top Runner Program, while the CFL patenting is only driven by fluorescent light efficiency standard (16.6% increase in lm/W (FY 1997 vs. FY 2005). The results provides evidence of a positive relationship between domestic energy-efficiency policies on domestic innovation, which supports Hypothesis 1.1.

Table 14 provides the estimation results on the impact of the United States lighting policy in the United States lighting innovation. Column (1)-(3) shows that POST×US is statistically significant at the 10% significance level for LED lighting. Column (4)-(6) shows no statistical significance for CFL lighting, suggesting that the impact of the Energy Policy Act of 2005 is not salient. Overall, the effect is not noticeable. In the case of the United States, Table 14 does not provide strong evidence of a positive relationship between domestic energy-efficiency policies on domestic lighting innovation which can be explained by the role of other countries' inventive activities. Both Tables also show some evidence of positive relationship between RD&D funding and lighting patenting, but evidence is weak.

Table 13. The impact of the Top Runner Program

	LED			CFL		
	YEAR FE (1)	Country FE (2)	Year/Country FE (3)	YEAR FE (4)	Country FE (5)	Year/Country FE (6)
JP	345.3***	295.5***	352.6***	178.6***	187.4***	194.0***
	(36.92)	(29.78)	(39.51)	(5.918)	(5.444)	(6.524)
POST	-80.58	6.425	-18.77	-11.63	2.754	-4.442
	(51.55)	(17.15)	(51.83)	(10.99)	(2.741)	(10.72)
POST×JP	1,747***	1,661***	1,723***	188.8***	172.6***	176.4***
	(206.2)	(267.3)	(235.6)	(14.79)	(19.10)	(15.81)
RD&D	0.122**	0.296***	0.145	0.0576***	0.0941***	0.0861***
	(0.0617)	(0.0906)	(0.0928)	(0.00863)	(0.0132)	(0.0125)
Electricity price	-0.0443	1.184**	-0.354	0.0877	0.174**	0.0583
	(0.305)	(0.476)	(0.548)	(0.0647)	(0.0826)	(0.0836)
Electricity consumption	14.69	-0.549	-0.722	1.602*	-0.741	-0.280
	(9.020)	(4.148)	(4.932)	(0.885)	(0.454)	(0.478)
GDP	62.66***	13.95	31.47	5.191*	2.046	3.985
	(20.61)	(14.05)	(28.31)	(2.915)	(1.856)	(3.275)
Constant	-58.11	-186.4*	15.30	-13.63	-31.10*	-22.96
	(56.78)	(100.4)	(103.0)	(9.885)	(16.04)	(15.76)
Year FE	YES	NO	YES	YES	NO	YES
Country FE	NO	YES	YES	NO	YES	YES
Observations	242	242	242	186	186	186
R-squared	0.737	0.867	0.883	0.915	0.965	0.969

Notes:

1. POST equals 1 after 1998.
2. JP indicates those whose inventor country location is Japan.
3. Observations indicate the number of countries multiplied by the number of years
4. Column (1) through (3): I restricted the sample to LED patents
5. Column (4) through (6): I restricted the sample to CFL patents.
6. Robust standard errors in parentheses
7. *** p<0.01, ** p<0.05, * p<0.1

Table 14. The impact of the Energy Policy Act of 2005

	LED			CFL		
	YEAR FE	Country FE	Year/Country FE	YEAR FE	Country FE	Year/Country FE
	(1)	(2)	(3)	(4)	(5)	(6)
US	-2,134***	-1,398***	-1,589***	-389.9***	-166.2***	-185.2***
	(272.6)	(317.2)	(313.4)	(31.13)	(30.22)	(27.65)
POST	-150.1	80.82	-86.52	-44.31*	9.212	-7.647
	(127.0)	(59.30)	(130.0)	(24.28)	(6.318)	(13.23)
POST×US	325.8*	258.9*	302.0**	41.46	19.57	22.72
	(173.6)	(135.7)	(135.3)	(34.31)	(19.83)	(18.41)
RD&D	3.837***	2.720***	2.949***	0.748***	0.378***	0.401***
	(0.443)	(0.513)	(0.520)	(0.0387)	(0.0445)	(0.0426)
Electricity price	0.562	1.031*	0.512	0.259***	0.164**	0.104
	(0.404)	(0.599)	(0.619)	(0.0919)	(0.0791)	(0.101)
Electricity consumption	12.29	-0.857	-3.457	2.022	-0.724	-0.587
	(9.855)	(6.996)	(8.666)	(1.383)	(0.852)	(0.972)
GDP	67.00***	8.455	37.82	4.354	1.846	5.518*
	(20.47)	(12.40)	(26.12)	(3.144)	(1.621)	(2.888)
Constant	-142.7*	-222.4**	-106.6	-22.13	-33.67**	-28.70*
	(76.14)	(109.4)	(105.5)	(20.68)	(13.42)	(16.02)
Year FE	YES	NO	YES	YES	NO	YES
Country FE	NO	YES	YES	NO	YES	YES
Observations	242	242	242	186	186	186
R-squared	0.644	0.779	0.799	0.805	0.936	0.944

Notes:
1. POST equals one after 2005.
2. The US indicates those whose inventor country location is the United States.
3. Observations indicate the number of countries multiplied by the number of years
4. Column (1) through (3): I restricted the sample to LED patents
5. Column (4) through (6): I restricted the sample to CFL patents.
6. Robust standard errors in parentheses
7. *** p<0.01, ** p<0.05, * p<0.1

3.4 Differential Impact for LED and CFL

3.4.1 Difference-in-difference-in-difference

As a robustness check, a triple difference-in-difference estimation provides sensitivity tests on our findings. Previously, Table 14 shows the differential impact of LED and CFL patents in response to the Energy Policy Act of 2005. To investigate further heterogeneity across two lighting technologies, a difference-in-difference-in-difference model is specified as:

$$No.of\ Patents_{i,t} = \beta_1 + \beta_2 Country_{i,t} + \beta_3 POST_t + \beta_4 LED_{i,t} + \beta_5 Country_{i,t} \times POST_t + \beta_6 Country_{i,t} \times LED_{i,t} + \beta_7 POST_t \times LED_{i,t} + \beta_8 POST_t \times LED_{i,t} \times Country_{i,t} + \beta\ X_{i,t} + \alpha_t + \gamma_i + \varepsilon_{i,t} \tag{6}$$

Where i=1,….,19 refers to the country and t=1992,…,2007 refers to time. The **Country** is the inventor country. **POST** indicates the period after the policy implementation. **LED** is a binary variable which indicates LED patents. Otherwise, it belongs to CFL patents. X are control variables: **RD&D** refers to energy efficiency RD&D expenditure. **ELEC** refers to the growth of household electric consumption. **PRICE_ELEC** refers to the electricity price data. **GDP** refers to the growth of Gross Domestic Product. **α** and **γ** each refer to time and country fixed effects. In addition, all the remaining errors are captured in the **ε**.

3.4.2 Estimation Results

Table 15 reports the estimation results on the triple difference-in-difference estimation results. Column (1)-(3) shows that **POST×JP×LED** is statistically positively significant. The results provide the evidence to support Hypothesis 1.2 that domestic policy positively influences foreign LED patenting, particularly Japanese patenting. Since the magnitude of the coefficient is large, it is plausible that Japanese inventors drive most of the LED innovations in response to the Energy Policy Act of 2005. Consistent with previous literature, the results show positive effect of RD&D funding on lighting patenting. It also confirms the induced innovation hypothesis that rising electricity prices positively affect energy-saving innovation. We also run the modified regressions, but we do not find any significant results: **POST×US×LED** and **POST×KR×LED**.

For the brevity of the paper, we report these results in the Appendix.

Table 15. The impact of the Energy Policy Act of 2005: policy certainty

	YEAR FE (1)	Country FE (2)	Year/Country FE (3)
POST×JP×LED	1,371***	1,343***	1,343***
	(257.1)	(261.6)	(255.2)
POST×LED	134.4**	162.8***	162.3***
	(54.86)	(46.13)	(46.66)
JP×LED	849***	849***	849***
	(241.6)	(244.0)	(240.1)
JP	231.0***	172.5***	211.3***
	(28.95)	(33.81)	(33.44)
POST	20.54	-101.3***	-39.06
	(62.27)	(36.50)	(58.64)
POST×JP	90.23***	133.9***	127.7***
	(25.36)	(37.71)	(32.81)
RD&D	0.276***	0.598***	0.551***
	(0.0686)	(0.136)	(0.127)
Electricity price	0.117	1.648***	1.049**
	(0.166)	(0.589)	(0.471)
Electricity consumption	5.446	-2.763	-4.240
	(6.912)	(4.412)	(5.552)
GDP	26.47**	-1.011	3.280
	(12.17)	(7.028)	(13.64)
Constant	-92.17*	-322.5***	-268.0**
	(49.67)	(114.1)	(105.8)
Year FE	YES	NO	YES
Country FE	NO	YES	YES
Observations	428	428	428
R-squared	0.647	0.734	0.742

Notes:

1. POST equals 1 after 2005
2. JP indicates those whose inventor country location is Japan.
3. Observations indicate the number of countries multiplied by the number of years
4. Robust standard errors in parentheses
5. *** p<0.01, ** p<0.05, * p<0.1

3.4.3 Difference-in-difference (policy uncertainty)

To further look into the effect of policy uncertainty, a difference-in-difference model is specified as:

$$No.of\ Patents_{i,t} = \beta_1 + \beta_2 Country_{i,t} + \beta_3 UNCERTAIN_t + \beta_4 LED_{i,t} + \beta_5 Country_{i,t} \times UNCERTAIN_t + \beta_6 Country_{i,t} \times LED_{i,t} + \beta_7 UNCERTAIN_t \times LED_{i,t} + \beta_8 UNCERTAIN_t \times LED_{i,t} \times Country_{i,t} + \beta\ X_{i,t} + \alpha_t + \gamma_i + \varepsilon_{i,t} \tag{7}$$

Where i=1,….,19 refers to the country and t=1992,…,2007 refers to time. The **Country** is the inventor country. **UNCERTAIN** indicates the period between the initial policy discussion and the final implementation: 2001-2004. **LED** is a binary variable which indicates LED patents. Otherwise, it belongs to CFL patents. $\boldsymbol{X}$ are control variables: **RD&D** refers to energy efficiency RD&D expenditure. **ELEC** refers to the growth of household electric consumption. **PRICE_ELEC** refers to the electricity price data. **GDP** refers to the growth of Gross Domestic Product. $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ each refer to time and country fixed effects. In addition, all the remaining errors are captured in the $\boldsymbol{\varepsilon}$.

3.4.4 Estimation Results

Table 16 reports the estimation results of the impact of policy uncertainty. Column (1)-(3), $UNCERTAIN$×JP×LED[71], shows a statistically significant positive result. The magnitude of the coefficient is less than the previous estimation results. Therefore, these results support Hypothesis 2.2, which indicates that domestic policy uncertainty positively affects foreign lighting innovation. To double-check findings, we include the triple difference-in-difference estimation results in the United States LED patenting in the Table 22 and Table 23. The evidence is not strong enough to support Hypothesis 2.1. We find the consistent results in RD&D funding. However, the effect of electricity price is mixed.

Table 16. The impact of the Energy Policy Act of 2005: policy uncertainty

	YEAR FE (1)	Country FE (2)	Year/Country FE (3)
$UNCERTAIN$×JP×LED	1,119***	1,094***	1,095***
	(333.4)	(357.1)	(350.6)
$UNCERTAIN$×LED	75.05**	100.2***	99.69***
	(32.52)	(33.03)	(33.28)
JP×LED	832.7***	832.7***	832.7***
	(271.3)	(276.2)	(274.5)
JP	222.8***	177.4***	219.8***
	(26.36)	(30.88)	(29.64)
UNCERTAIN	33.69	-63.48**	-15.32
	(53.90)	(29.22)	(52.51)
$UNCERTAIN$×JP	107.3***	70.55	93.80**
	(40.34)	(44.76)	(43.84)
RD&D	0.225***	0.549***	0.444***
	(0.0631)	(0.132)	(0.116)
Electricity price	-0.00561	1.834***	0.570
	(0.171)	(0.538)	(0.435)
Electricity consumption	10.93*	-0.0353	1.716
	(6.217)	(3.965)	(4.639)
GDP	20.53*	2.788	-2.331
	(10.73)	(6.830)	(11.38)
Constant	-74.00	-344.7***	-193.2*
	(47.03)	(112.1)	(100.2)
Year FE	YES	NO	YES
Country FE	NO	YES	YES
Observations	428	428	428
R-squared	0.628	0.706	0.715

Notes:
1. UNCERTAIN equals one if the year of application is between 2001 and 2004.
2. JP indicates those whose inventor country location is Japan.
3. Observations indicate the number of countries multiplied by the number of years
4. Robust standard errors in parentheses
5. *** p<0.01, ** p<0.05, * p<0.1

Previously, we coded the policy uncertainty as a binary variable. This is obviously not the best representation form of the policy uncertainty. However, it is almost impossible to capture all those aspects of policy uncertainty with a single metric. In this paper, we use a coefficient of variation of R&D expenditure as a proxy of policy uncertainty to measure country-level RD&D investment variability (Czarnitzki & Toole, 2011; Kalamova, Johnstone, & Hascic, 2012). The coefficient of variation is frequently used to measure dispersion which takes the absolute value of the standard deviation, normalize it by the mean in equation (8).

$$Policy\ uncertainty_{i,t} = \frac{\sqrt{\frac{1}{5} \times \sum_{s=0}^{4}[RD\&D_{i,t-s} - (\frac{1}{5}\sum_{s=0}^{4} RD\&D_{i,t-s}))]}^{2}}{\frac{1}{5}\sum_{s=0}^{4} RD\&D_{i,t-s}} \tag{8}$$

Where t is a year and i indicates a country, and RD&D indicates RD&D expenditure.

Figure 9 displays the measures of policy uncertainty for the U.S. and Japan.[72] The most notable feature in this Figure is that there is a huge unpredictability in Japan in the 1990s while the U.S. policy uncertainty slightly grows between 2001 and 2005. Compared to this spike in 1994, the U.S. change much lower.

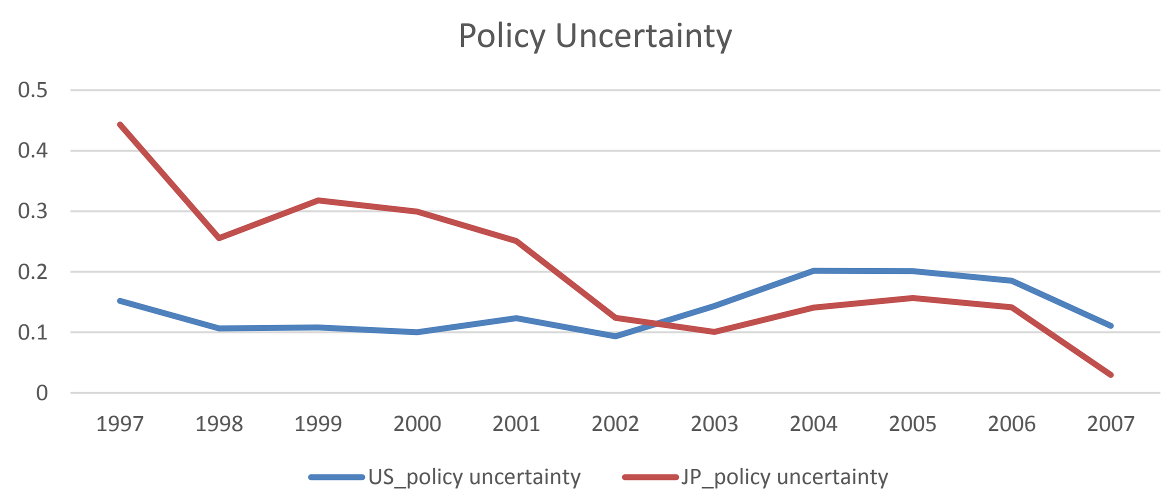

Figure 9. A measure of policy uncertainty[73]

[72] Since South Korea's RD&D expenditure data is not available before 2001, we do not include it in this graph.
[73] U.S. and Japan policy uncertainties are statistically significantly different at the 0.05 level.

In the following regression analysis, we expect the sign of the coefficients to be negative because domestic policy uncertainty can negatively affect domestic innovation. Table 17 shows the estimation results. Panel A demonstrate the effect of contemporary policy on innovation, while Panels B and C indicate the effect of one-year lag, two-year lag, respectively. The coefficients of interest are a triple difference.

While there is a significant negative relationship between Japan's policy uncertainties on Japanese innovation, the effect of U.S. policy uncertainties on U.S. innovation is not significant. This exercise reveals that Japan's inventing behavior is more responsive to RD&D funding variability than those of U.S. However, the effects of U.S. RD&D are highly significant in the contemporary regression and with one and two-year lags.

The effect of policy uncertainty fades away as time passes by, but the effect of one-year lag is the highest among three estimation results. To check the robustness of the models, we restrict the sample between 2000-2004, and 2001-2005. The negative and significant findings of the effect of Japan's policy uncertainty are consistent with the previous findings.

Table 17. Difference-in-Difference-in-Difference Estimation Results of Policy Uncertainty

	US_contemp	JP_contemp	US_1year_lag	JP_1year_lag	US_2year_lag	JP_2year_lag
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Contemporary Effect						
Pol_uncertainty	-122.6**	-43.21**				
	(60.23)	(20.35)				
Pol_uncertainty×US	578.1					
	(352.0)					
Pol_uncertainty×LED	-117.2*	15.08				
	(64.25)	(22.64)				
Pol_uncertainty×US×LED	-174.7					
	(428.5)					
Pol_uncertainty×JP		-15.93				

Table 17 continued						
		(97.26)				
Pol_uncertainty×JP×LED		-1,928***				
		(514.0)				
Panel B. One-year Lag						
Pol_uncertainty1 Table 17 Continued			-133.9**	-31.89*		
			(58.21)	(16.63)		
Pol_uncertainty1×US			698.5***			
			(265.5)			
Pol_uncertainty1×LED			-88.78	26.78		
			(64.65)	(22.61)		
Pol_uncertainty1×US×LED			-128.4			
			(693.7)			
Pol_uncertainty1×JP				-50.21		
				(84.74)		
Pol_uncertainty1×JP×LED				-3,218***		
				(693.2)		
Panel C. Two-year Lag						
Pol_uncertainty2					-103.0*	-14.26
					(59.60)	(17.40)
Pol_uncertainty2 ×US					694.7**	
					(351.0)	
Pol_uncertainty2×LED					-88.67	3.955
					(59.87)	(17.77)
Pol_uncertainty2×US×LED					-318.2	
					(444.4)	
Pol_uncertainty2×JP						-31.50
						(115.1)
Pol_uncertainty2×JP×LED						-1,988***
						(554.8)
Panel D. Control Variables						
US	-758.8***		-857.2***			
	(269.1)		(273.0)			
LED	185.1***	45.18***	172.9***	35.09***	168.1***	38.85***
	(44.84)	(9.316)	(43.92)	(7.961)	(42.43)	(8.702)
US×LED	-16.94		-5.749		24.95	
	(103.8)		(141.7)		(117.1)	
JP		223.5		275.1		161.9
		(166.4)		(171.3)		(214.7)
JP×LED		1,921***		2,253***		2,012***
		(250.8)		(232.0)		(267.5)
RD&D	1.398***	0.482	1.485***	0.367	1.493***	0.654
	(0.403)	(0.332)	(0.414)	(0.335)	(0.420)	(0.428)
Electricity price	0.338	0.147	0.121	0.0299	0.0107	0.0380
	(0.437)	(0.240)	(0.420)	(0.215)	(0.396)	(0.230)
Electricity consumption	1.827	3.300	0.596	-1.289	-0.363	-1.750
	(6.862)	(2.963)	(6.770)	(1.882)	(6.820)	(2.749)
GDP	24.38	21.38	20.09	15.96*	23.63	25.35**
	(15.97)	(14.36)	(14.90)	(8.269)	(15.28)	(11.03)
Constant	-120.8	-77.39*	-113.2	-93.26*	-142.2*	-

Table 17 continued						
						110.1**
	(78.63)	(45.21)	(71.94)	(53.00)	(74.02)	(54.49)
Observations	412	412	410	410	408	408
R-squared	0.582	0.843	0.593	0.894	0.577	0.865
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES

Notes:
1. Pol_uncertainty 1 indicates policy uncertainty one-year lag.
2. Pol_uncertainty 2 indicates policy uncertainty two-year lag.
3. Robust standard errors in parentheses
4. *** p<0.01, ** p<0.05, * p<0.1
5. 1992-2007

3.5 Discussion

This paper exploits two quasi-experiments in lighting technology to identify the impact of energy-efficiency policies on CFL and LED innovation. The first quasi-experiment (e.g., the Top Runner Program) allows us to explore two hypotheses: the effect of the domestic energy-efficiency policy on domestic lighting patenting, and the effect of domestic energy-efficiency policy on foreign lighting patenting.

The second quasi-experiment (e.g., the Energy Policy Act of 2005) enables us to identify four hypotheses addressing the effect of domestic energy-efficiency policy on domestic lighting patenting, the effect of domestic energy-efficiency policy on foreign lighting patenting, the effect of domestic policy uncertainty on foreign lighting patenting, and the effect of domestic policy uncertainty on domestic lighting patenting. For simplicity, only significant results are discussed below.

The quasi-experiments produce strong evidence that the Top Runner Program positively affects Japanese lighting patenting: CFLs and LEDs. However, we only find a significant positive relationship between the Energy Policy Act of 2005 on the United States LED patenting at the 10% significance level. Our results indicate that the Energy Policy Act of 2005 was a significant driver of LED innovation, while the evidence is weak on CFL innovation. Domestic energy-efficiency policy positively affects domestic lighting patenting.

In order to identify the effect of domestic energy efficiency policy on foreign lighting is patenting, we further explore the differential impact of the Energy Policy Act of 2005 on lighting patenting. We find strong evidence that the Energy Policy Act of 2005 positively affected Japanese lighting patenting. Consistent with previous studies, we show that domestic energy-efficiency policy can be an effective policy tool to drive foreign lighting patenting.

We also find evidence of patenting surges after the initial discussion in 2001 of the Energy Policy Act of 2005. So, it is evident that there is a statistically significant policy-inducement effect, but patenting started to increase earlier than the actual implementation of the policy in 2005.

However, we cannot find any evidence to support the effect of policy uncertainty of the U.S. Energy Policy Act of 2005 on domestic lighting patenting. So, what we can conclude from these findings is that firms are constantly innovating, and they are filing patent applications not only in response to the policy change but also for various reasons such as licensing activities, catching investors, and blockading competitors.

When it comes to the effect of policy uncertainty on lighting patenting, we find the negative and significant effect of Japan’s policy uncertainty on Japan’s lighting innovation. Over several decades, the Japan’s RD&D expenditure was more volatile than the U.S. expenditure, so this funding variability negatively affects Japan’s LED innovation.

Note the total number of patent applications filed by Japanese inventors is relatlvey flatter than the those of U.S. inventors over the years.[74] This validates our estimation results in two ways. First, a very sharp increase by Japanese inventors was not driven by the general national trend, but the impact of the policy change. Second, the increaseing number of patents in the U.S. implies the overestimation of our results that also validate our non-significant results by U.S. inventors.

The limitation of this paper is as follows. We mainly focus on the impact of three countries energy efficiency policy on innovation because these countries file the majority of patents. However, it is possible that European countries can also play a significant role in inducing these technologies. We further relax this assumption to incorporate the entire scope of the countries. For example, the United Kingdom implemented a plan to phase out traditional light bulbs by 2012. After that, most EU countries agreed to implement an incandescent light bulb phase out (Waide & Tanishima, 2006; Waide, 2010).

The potential measurement error leads to attenuation bias using a binary indicator of whether a country had an energy-efficiency policy or not as the policy variable is well addressed in Anin Aroonruengsawat, Maximilian Auffhammer, & Sanstad (2012)'s paper. Their paper hand coded new building permits from Census Bureau sources in order to overcome issues by incorporating the heterogeneity in policy intensity, stringency, and enforcement. This is in the area of future research.

3.6 Conclusions

[74] http://blog.nycdatascience.com/student-works/research-and-development-performance-in-select-countries/

First, this paper identifies the impact of the domestic energy efficiency policy on domestic lighting patenting in the case of Japan and the U.S. Though there is a significant positive relationship between Japanese energy efficiency policy on Japanese lighting patenting, the evidence is weak concerning the U.S.'s energy efficiency policy on U.S. lighting inventive activities. This is because the Energy Policy Act of 2005 provided some incentives for energy efficiency improvement, but it did not regulate the lighting industry and lighting industry products. Later, the Energy Independence and Security Act of 2007 (EISA) phased out incandescant light bulbs, which significantly changed the U.S. lighting industry.

Second, this paper presents evidence that domestic energy efficiency policy stimulates foreign energy efficiency lighting patenting in the case of the Energy Policy Act of 2005. The domestic energy efficiency policy can be a significant driver of foreign patenting because Japan accounts for the largest LED lighting market share, at 26% in 2014.[75] In a nutshell, Japanese inventors have greater responsiveness to environmental policy changes.

Third, we find strong evidence of the adverse effect of Japan's policy uncertainty on Japan's LED innovation. However, we cannot find any significant evidence that U.S. policy uncertainty negatively affects U.S. LED patenting. To investigate the reason U.S.RD&D expenditure is not a signficant factor on U.S. LED patenting, we need to investiage the relationship between firms' R&D expenditure and government R&D expenditure. This is an area for future research.

[75] http://www.digitimes.com/news/a20140107PD202.html

Lastly, energy-efficiency standards create demand for environmental innovation, and firms innovate themselves to produce more energy-efficient goods and services (Vollebergh & van der Werf, 2014). Policy makers should pay attention to international dimensions of energy-efficiency standard setting because policy and innovation is interwined in an international domain. Therefore, a salutary process that promises to strengthen standards internationally and steady investment in RD&D can spur domestic energy innovation.

Table 18. Lighting policies across countries

Country	Year	Policy	Contents
United States	**2003**	S&L R&D Project	2003-2005
	2005	Energy Policy Act of 2005	Solid-State Lighting Program Minimum standards for bare and covered medium screw base self-ballasted CFLs manufactured for use in the U.S.
	2007	The Energy Independence and Security Act of 2007 (EISA)	It began phasing out 100W incandescent light bulbs in 2012, 75W in 2013, and 40 & 60W in 2014, consequentially.
Japan	**1993**	Efficiency standards for fluorescent lamps	The government called for an improvement in energy efficiency by 2000 of 3–7% compared to the level of 1992.
	1998	21st Century Lighting Project	Promoting its semiconductor lighting technology 1998-2002
	1998	**Top Runner Program of the Energy Conservation Law**	To improve energy efficiency of end-use products e.g.) Fluorescent lights: 16.6 % increase in lm/W (FY 1997 vs. FY 2005)
South Korea	**2001**	Semiconductor lighting national program	1993-1996, 1999-2000, 2001
	2004	Replacement of 40W fluorescent lamps with 32W fluorescent lamps	The increase of the MEPS standard (66 lm/W -> 80 lm/W) for 40W fluorescent lamps in January 2004 accelerated the replacement of 40W fluorescent lamps with 32W fluorescent lamps.
	2006	LED Lighting 15/30 Dissemination Project	It aims to increase the share of LED lights to 30% by 2015 (Ministry of Knowledge Economy)

Sources:
U.S. Congress. 109th Congress. (2005, Aug. 8)., Pub. L. 109-58, Energy Policy Act of 2005, Available: http://www.gpo.gov/fdsys/pkg/PLAW-109publ58/pdf/PLAW-109publ58.pdf.
https://www.energystar.gov/ia/products/lighting/cfls/downloads/EISA_Backgrounder_FINAL_4-11_EPA.pdf
https://www.iea.org/publications/freepublications/publication/light2006.pdf
http://www.lrc.rpi.edu/education/outreachEducation/pdf/CLE4/AM_FedStateLegislation.pdf

Table 19. International Patent Classification (IPC) related to lighting technologies

Lighting	Category	Description	Sources
Incandescent	F21H	Incandescent lamp	OECD
CFL	H01J 61	Gas- or vapor-discharge lamps (Compact Fluorescent Lamp)	
LED	F21K9	Electric lamps using semiconductor devices as light generating element, e.g., using light emitting diodes (LED)	
	H05B33	Lighting-Electroluminescent light (LED) sources	(Simons & Sanderson, 2011), OECD
	H01L33/00	Semiconductor devices for light emission, including manufacture and details thereof	(Simons & Sanderson, 2011)
	G09G3/30	Circuits for readable displays using electroluminescent panels	
	G09G3/32	As G09G3/30, using semiconductors	
	G09F9/33	Pixel-based displays using semiconductors	
	H01L 27/15	Solid-state circuitry incorporating semiconductor light-emitting devices	
	G09G3/14	As G09G3/32, but for displaying a single character	

Table 20. Number of Patents for Both LEDs and CFLS, by Country of Inventors (1992-2007)

Country	No. of patents	Percent (%)	No. of patents	Percent (%)
AT	108	0.3%	18	0.2%
AU	42	0.1%	2	0.0%
BE	83	0.2%	76	0.9%
CA	329	0.8%	25	0.3%
CH	1,505	3.7%	328	3.7%
DE	1,732	4.2%	967	10.9%
DK	64	0.2%	18	0.2%
ES	30	0.1%	3	0.0%
FI	43	0.1%	0	0.0%
FR	282	0.7%	44	0.5%
GB	543	1.3%	79	0.9%
IT	107	0.3%	22	0.2%
JP	23,361	56.8%	5,260	59.5%
KR	9,835	23.9%	872	9.9%
NL	435	1.1%	370	4.2%
NO	5	0.0%	0	0.0%
NZ	3	0.0%	0	0.0%
SE	27	0.1%	11	0.1%
US	2,590	6.3%	745	8.4%
Total	41,124	100.0%	8,840	100.0%

*AT (Austria), AU (Australia), BE (Belgium), CA (Canada), CH (Switzerland), DE (Germany), DK (Denmark), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), IT (Italy), JP (Japan), KR (Korea) , NL (Netherlands), NO(Norway), NZ (New Zealand), SE (Sweden), and US (United States)

*Source: http://www.wipo.int/pct/guide/en/gdvol1/annexes/annexk/ax_k.pdf

Table 21. Summary Statistics: key variables

	Mean	Std.	Min	Max	Unit
Filing year	2002.839	3.718683	1992	2007	Year
US	0.070968	0.2567741	0	1	Percentage (1)
JP	0.609048	0.4879688	0	1	Percentage (1)
KR	0.16462	0.3708414	0	1	Percentage (1)
RDD	339.9436	222.8748	0	752.318	Million USD (2013 prices and PPP)
RDD1	333.6072	233.3377	0	752.318	Million USD (2013 prices and PPP)
RDD2	325.9584	241.7883	0	752.318	Million USD (2013 prices and PPP)
ELEC_Price	146.7481	30.70582	52.858	253.834	USD PPP/MWh
ELEC_Con	2.497427	2.629535	-12.6312	10.71921	Percentage Change
GDP	2.153551	1.663093	-3.3	6.3	Percentage Change
N	46993				

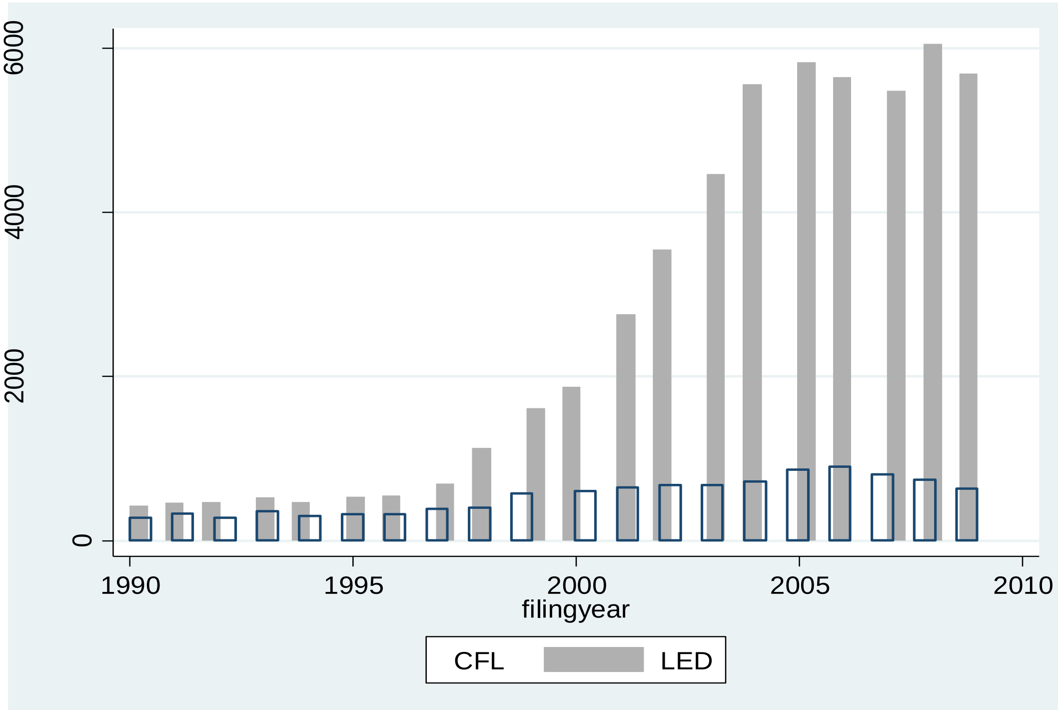

Figure 10. CFL & LED Patent applications per year: extended patent family

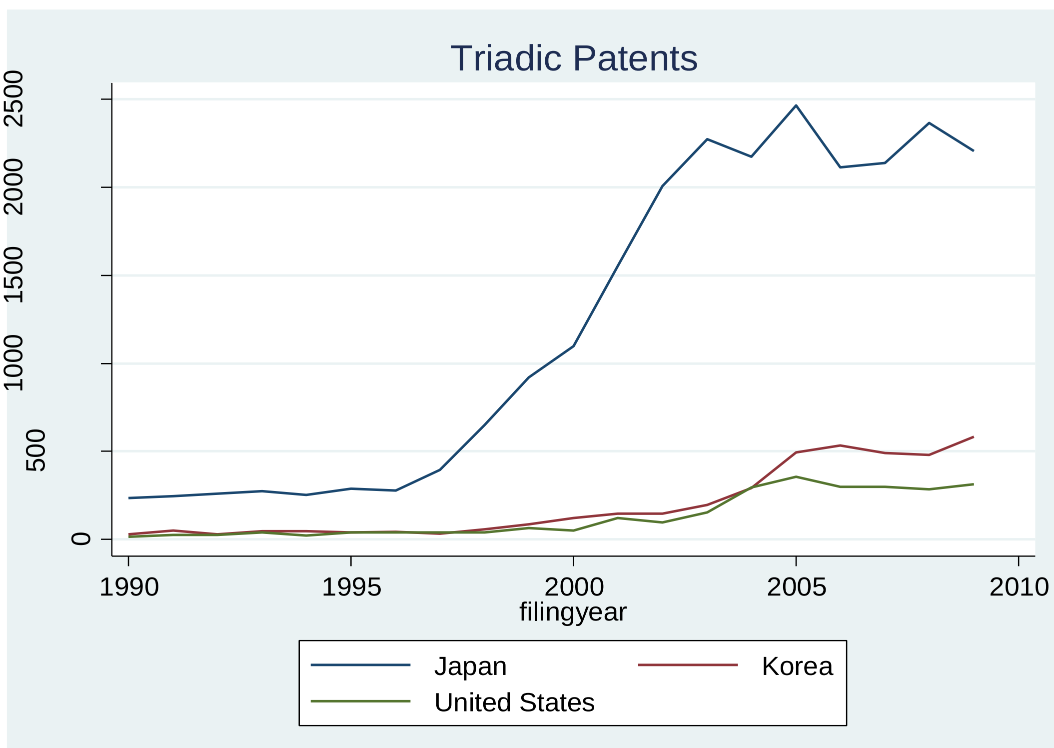

Figure 11. Triadic patents by fractional country counts

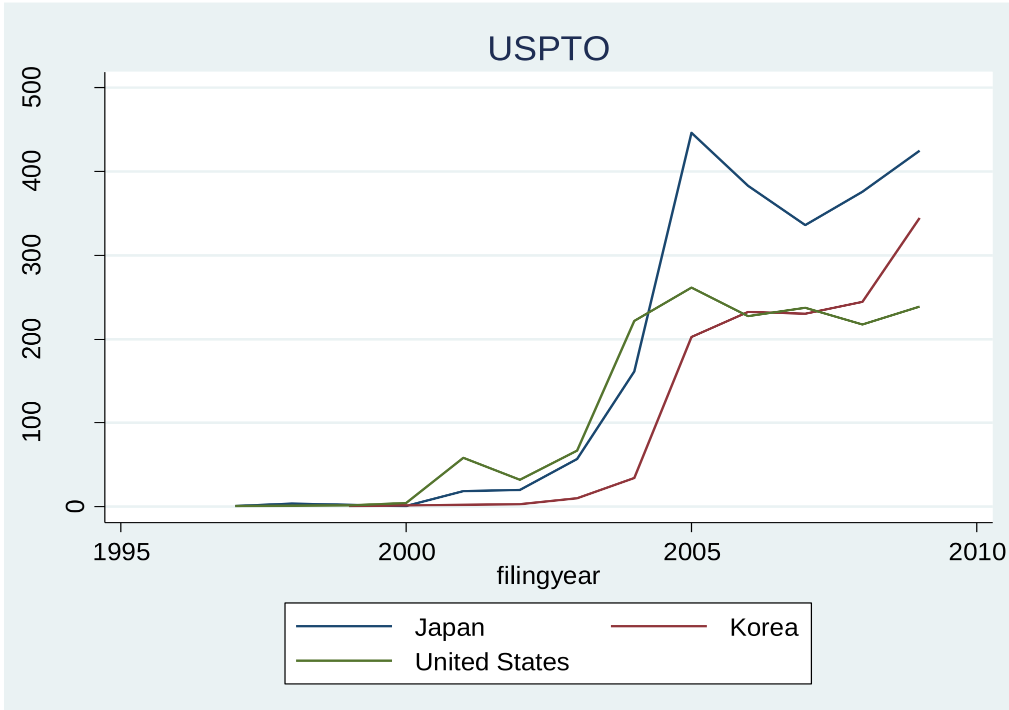

Figure 12. USPTO patents by fractional country counts

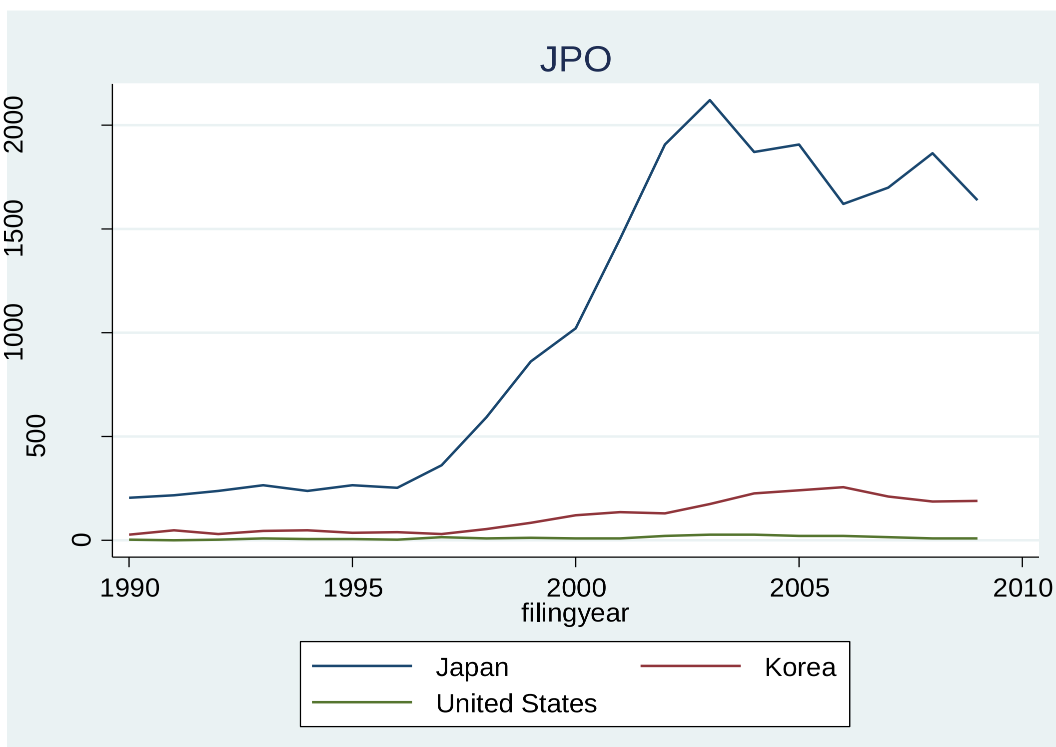

Figure 13. JPO patents by fractional country counts

Table 22. The impact of the Energy Policy Act of 2005 on domestic patenting: policy certainty

	YEAR FE (1)	Country FE (2)	Year/Country FE (3)
POST×US×LED	-48.82	-75.06	-73.68
	(157.0)	(125.8)	(120.4)
POST×LED	270.4***	296.6***	295.2***
	(83.00)	(79.16)	(80.26)
US×LED	73.77	73.77	73.77
	(80.59)	(75.20)	(63.11)
US	-1,314***	-826.2***	-934.0***
	(233.6)	(238.2)	(263.7)
POST	-165.9**	-115.9**	-132.0
	(83.01)	(50.63)	(83.86)
POST×US	220.8*	189.5**	210.7**
	(114.1)	(89.21)	(94.90)
RD&D	2.313***	1.563***	1.692***
	(0.401)	(0.403)	(0.440)
Electricity price	0.447*	0.665	0.304
	(0.256)	(0.539)	(0.455)
Electricity consumption	7.659	-1.393	-2.371
	(7.688)	(5.960)	(7.322)
GDP	40.20***	6.037	24.00
	(14.43)	(8.511)	(18.45)
Constant	-96.08**	-136.5	-76.44
	(45.71)	(95.47)	(77.45)
Year FE	YES	NO	YES
Country FE	NO	YES	YES
Observations	428	428	428
R-squared	0.458	0.538	0.550

Notes:
1. POST indicates after the Energy Policy Act of 2005.
2. The U.S. indicates those whose inventor country location is the United States.
3. Observations indicate the number of countries multiplied by the number of years
4. Robust standard errors in parentheses
5. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 23. The impact of the Energy Policy Act of 2005 on domestic patenting:

policy uncertainty

	YEAR FE (1)	Country FE (2)	Year/Country FE (3)
POL_UNCERTAINTY×US×LED	-131.5	-157.3	-155.3
	(214.7)	(191.8)	(169.3)
POL_UNCERTAINTY ×LED	211.4***	237.2***	235.2***
	(63.74)	(63.87)	(64.35)
US×LED	95.33	95.33	95.33
	(75.87)	(70.86)	(61.09)
US	-1,279***	-771.7***	-900.8***
	(221.3)	(213.0)	(238.1)
POL_UNCERTAINTY	-120.5	-100.3**	-99.11
	(77.77)	(44.95)	(77.28)
POL_UNCERTAINTY ×US	68.06	86.87	80.07
	(133.4)	(117.1)	(101.3)
RD&D	2.294***	1.548***	1.658***
	(0.393)	(0.376)	(0.410)
Electricity price	0.355	1.154**	0.135
	(0.247)	(0.470)	(0.394)
Electricity consumption	8.996	-2.489	-0.867
	(7.359)	(5.829)	(6.982)
GDP	36.59***	9.995	21.27
	(13.62)	(9.701)	(16.88)
Constant	-86.89**	-217.6**	-59.24
	(43.33)	(88.66)	(69.53)
Year FE	YES	NO	YES
Country FE	NO	YES	YES
Observations	428	428	428
R-squared	0.448	0.527	0.541

Notes:
1. POL_UNCERTAINTY equals 1 if the year of application is between 2001 and 2004.
2. The U.S. indicates those whose inventor country location is the United States.
3. Observations indicate the number of countries multiplied by the number of years
4. Robust standard errors in parentheses
5. *** p<0.01, ** p<0.05, * p<0.1

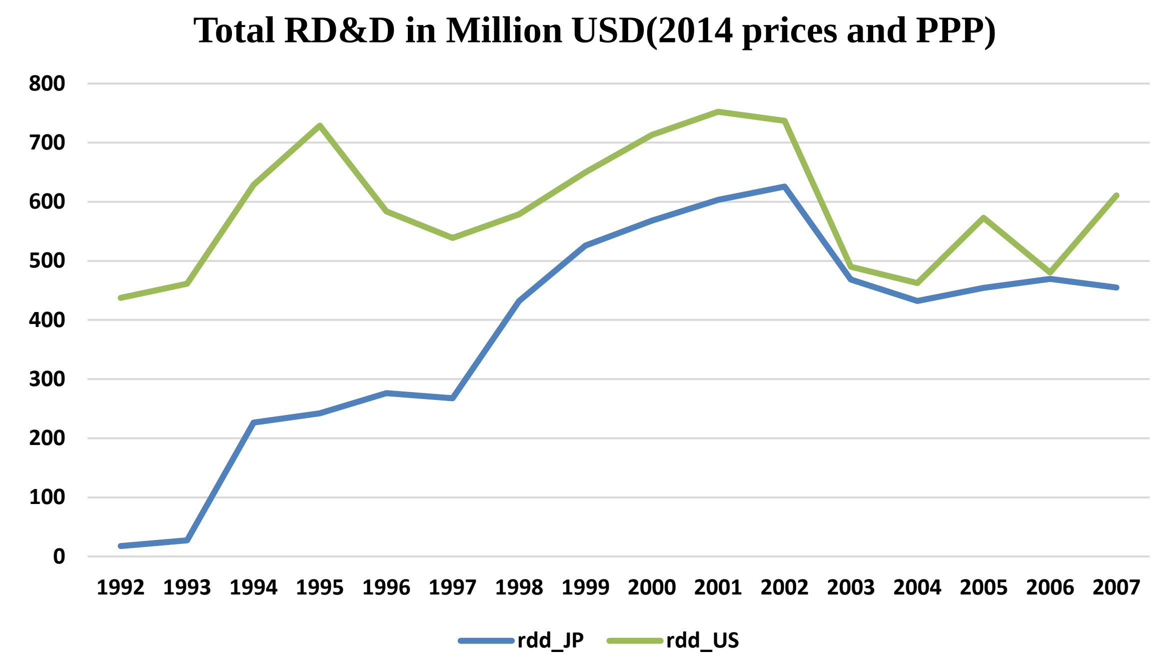

Figure 14. Total RD&D

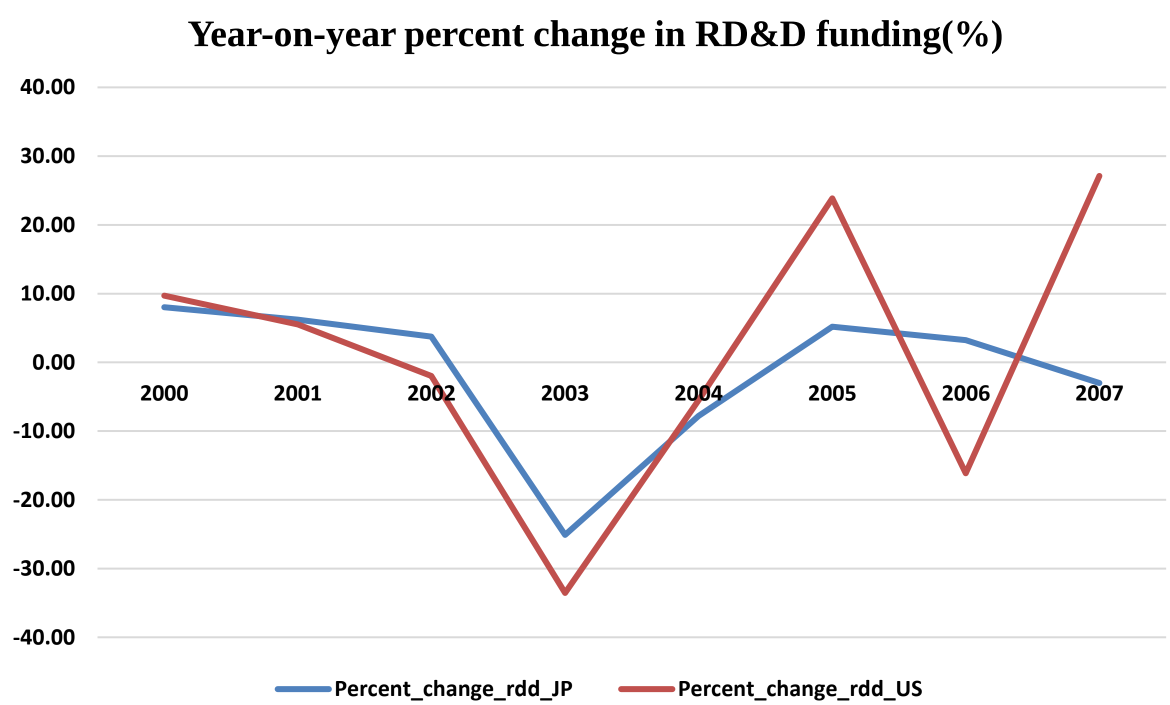

Figure 15. Year-on-year percent change in RD&D funding

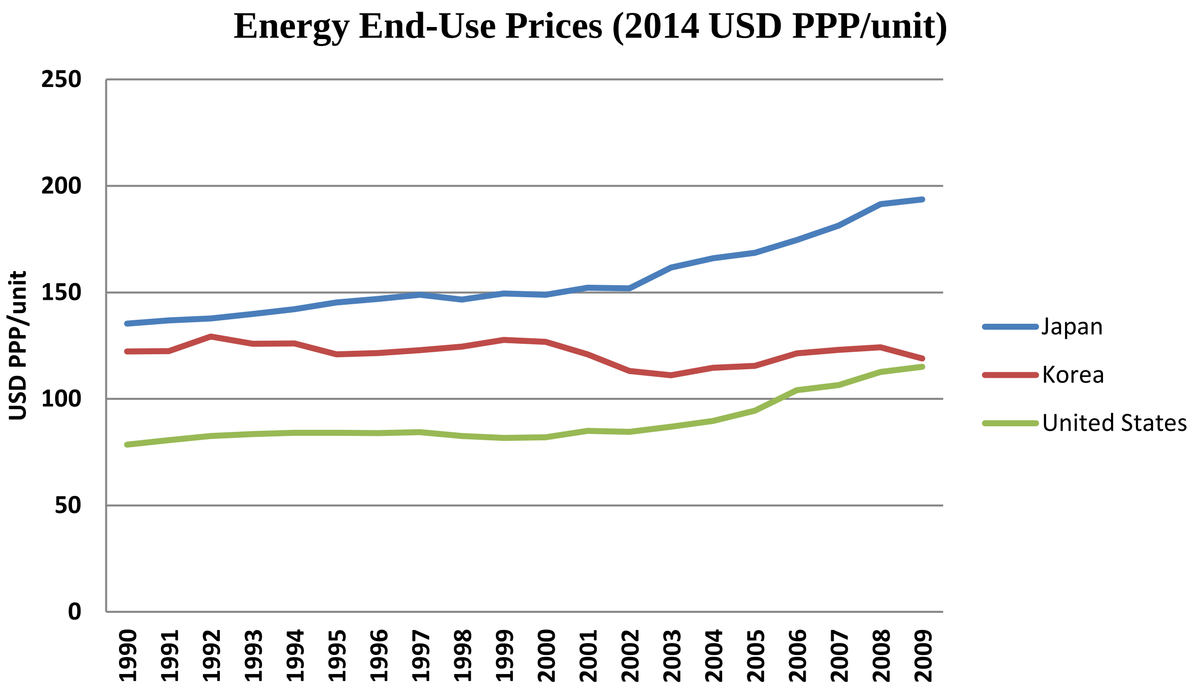

Figure 16. Energy End-use prices

Table 24. Correlation Matrix (Full Sample)

	Filing year	US	JP	KR	RDD	RDD1	RDD2	Elec_price	Elec_con	GDP
Filing year	1									
US	-0.0482	1								
JP	-0.1619	-0.345	1							
KR	0.3137	-0.1227	-0.5541	1						
RDD	0.0005	0.2941	0.6847	-0.5258	1					
RDD1	0.0579	0.2808	0.6712	-0.5338	0.9597	1				
RDD2	0.1307	0.2998	0.6341	-0.5295	0.9054	0.9597	1			
Elec_price	0.238	-0.4993	0.5761	-0.4078	0.221	0.2488	0.2567	1		
Elec_con	-0.0152	-0.0112	-0.1531	0.4316	-0.1934	-0.2822	-0.2238	-0.2667	1	
GDP	0.4233	0.133	-0.6275	0.725	-0.4874	-0.4241	-0.3686	-0.3634	0.2543	1

CHAPTER 4. GASOLINE PRICES, BELIEFS, AND THE ENERGY EFFICIENCY

4.1 Introduction

Energy issues and greenhouse gas emissions present the current generation with intertwined challenges. One partial response to these obstacles is the development and deployment of more energy-efficient vehicles such as hybrid or plug-in hybrid vehicles. However, recent low gasoline prices pose challenges to consumers who may adopt alternative vehicles. For example, deliveries of plug-in electric vehicles in the United States decreased 17 percent in 2015 compared to 2014, possibly due to the lower price of gasoline at the pump. To increase the number of alternative vehicles to a level that could have a meaningful impact on climate change requires an understanding of how consumers' belief on future gasoline prices affect the willingness to buy more fuel-efficient vehicles.

Compared to electricity prices, gasoline prices are more visible to the consumer since we can easily see the price at gas stations and are frequently exposed to gas prices on radios or televisions. So, obtaining gasoline price information is not costly. Given this information, it is plausible that consumers form future gasoline price beliefs. Anderson, Kellogg, and Sallee (2013) and Allcott (2011) showed that consumers could make reasonable forecasts of average future energy prices which means that tomorrow's gasoline price would be the same as today's price. The same assumption was made in the automobile economics literature (Kahn, 1986; Bento, Li, & Roth, 2012; Klier & Linn, 2012). Gallsagher and Muehlegger (2011) also made the same assumption when they calculated implicit discount rates. Regardless of whether this assumption is valid or not[76], if people form future gasoline price beliefs (Manski, 2004), these beliefs may affect their willingness to buy more energy-efficient cars.

Theoretically, different scholars proposed numerous theories that explain the consumption of environmentally friendly goods. A traditional neo-classical economics theory posits rational human actors who aim to maximize their own utilities when they make decisions about energy-efficient technologies. On the other hand, the most frequently used theory in social sciences is the Theory of Reasoned Action (TRA) which posits that behavioral intentions are a function of a belief about the likelihood of a particular outcome (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975).

Along the similar lines, Kahneman (2002) explained two types of cognitive processes. The first type is an intuitive one, in which a person makes choices without forming an explicit belief. The second type is a rational cognitive process, which requires forming an explicit future belief, and then a consumer makes a decision based on this belief. It is still arguable which type applies to forming beliefs on prices, but it is possible that a consumer goes through the second cognitive process, especially in the automobile market.

This mechanism is shown in a variety of different contexts (Bollinger, Leslie, & Sorensen, 2011; Jensen, 2010). Hensher (1982) argued that future gasoline price perception could be a significant factor in the adoption of electric vehicles. Particularly, Curtin, Shrago, and Mikkelsen (2009) found that higher future gas prices are associated with a higher likelihood of buying plug-in hybrid vehicles, using the Michigan Survey of Consumers. However, their study

[76] Anderson, Kellogg, and Sallee (2013) argued that this is a valid assumption.

is not clear about the difference between five-year/one-year future expected gasoline prices in regard to the likelihood of buying a hybrid vehicle which is the primary goal of this chapter. Here we can ask the following question: which one, five-year expected prices or one-year expected prices, better predicts the likelihood of buying more fuel-efficient cars?

This paper investigates whether future gasoline price beliefs affect the willingness to purchase more fuel-efficient vehicles, such as hybrid and plug-in hybrid vehicles. Relatively few studies focus on how consumers' future expectations of gas prices affect their willingness to consider alternative vehicles. If people have a perception of low future gasoline prices, it increases the consumer's payback period which negatively impacts return on investment (ROI). Therefore, people are less likely to buy more fuel-efficient cars. This study can fill the gap in understanding consumers' attitudes toward the future cost of gasoline prices and their purchasing intention on more fuel-efficient vehicles. Though revealed preference methods are better than stated preference methods because people reveal their values with their behaviors, the limitations of stated preference research design is obvious: What people say is not the same as what they actually do (Train, 2009). However, using this unique dataset will allow us to explore meaningful research questions.

It is widely acknowledged that if the price of gasoline increases, the demand for gasoline decreases. Extensive studies have discovered the price elasticity of demand for petrol. Goodwin, Dargay, and Hanly (2004) summarized sixty-nine published literature of the price elasticity of demand for gasoline, and present price elasticity ranges from 0.00 to -1.81 depending on the estimation method and data. Wadud, Graham, and Noland (2010) estimate the short-run price elasticity of demand ranges from -0.03 to -0.34, which is an inelastic demand in the short run, as we already know. Concerning the elasticity of supply, fuel taxes, and fuel economy standards assume the price elasticity of supply of 2.0, which comes from a U.S. Energy Information Administration (EIA) report. Coyle, DeBacker, and Prisinzano (2012) have provided both the price elasticity of demand and supply of gasoline using the same data source and compatible models. This study found that demand elasticities are in line with the previous literature, and the price elasticity of supply is 0.29, which differs from the common assumption of a perfectly inelastic short-run supply curve. Literature about the sensitivity of gasoline consumption to changes in prices has been investigated by Dahl and Sterner (1991) and Greene, Kahn, and Gibson (1999).

These initial studies provide the fundamental understanding of the sensitivity of consumer behaviors to the change of gasoline prices. Most found that higher gas prices lead to increased demand for smaller, more fuel-efficient cars, especially if higher gas prices are sustained (Congressional Budget Office, 2008). Higher gas prices would influence consumers' automobile purchasing habits in the long run. As an example, it was empirically proven that the market share of light trucks decreased between 2004 (55% of the passenger vehicle market) and 2006 (52% of the passenger vehicle market) due to the increase in gasoline price. The longer the gas prices remain high; the more likely consumers are to switch their overall automobile purchasing behaviors. Consumers might switch their vehicles to more fuel-efficient vehicles if the price of gasoline remains higher than the historical average price. Li, Haefen, and Timmins (2008) also showed that high gasoline price affects the purchase of more fuel-efficient vehicles and speeds the scrapping of less fuel-efficient vehicles.

However, other studies have argued that the impact of higher gasoline prices on purchasing fuel-efficient vehicles may not be as significant as once thought. It might be that uncertainties about future fuel savings are considerable barriers to the purchase of fuel-efficient vehicles (Tversky & Kahneman, 1992). That is, consumers are reluctant to buy fuel-efficient vehicles unless the return is sufficiently high and the payback time is short. Allcott and Wozny (2009) found that people underestimate future gas costs when they purchase automobiles and weigh immediate losses more heavily than future gains in uncertain situations; thus, the probability of loss (the initial electric vehicle price) is usually exaggerated (Kahneman & Knetsch, 1991). As a rule of thumb, consumers usually count losses approximately twice as much as gains when they make decisions (DellaVigna, 2007). Furthermore, consumers have a very low awareness of how much fuel they use over time (Turrentine & Kurani, 2007). Unless future gasoline prices rise so dramatically that people can easily envision future fuel savings, they are less likely to consider purchasing more fuel-efficient vehicles because they do not fully account for the benefit of future fuel savings.

In this paper, we find significant evidence that current gasoline prices matter in regard to the willingness to buy hybrid vehicles. Further, we find that the long-term future gas price beliefs have more of an impact on buying hybrid vehicles than the short-term gas price beliefs. Since price incentive works, this finding is relevant to the policy rationale for a gasoline tax. The rest of the paper is organized as follows. First, the survey data are described. Second, we describe the methods and model specification. Third, we provide the results and discussion. Fourth, we address the implications and then conclude.

4.2 Methods

4.2.1 Data

We pooled monthly data from the Michigan Survey of Consumers (MSC)[77] that was conducted from July 2008 to November 2008. It is well known for eliciting beliefs on future economic conditions and widely used. The survey involved telephone sampling from a representative sample of 500 U.S. households each month. This survey data was previously used in Anderson et al., (2013). Missing values and "refused" responses reduced the sample size to 1211. For other variables, we considered "don't know" as at least some kind of answer, so we did not consider it as a purely missing value. We dropped all observations that included "don't know" and "N/A." We discussed the treatment of purely missing values in robustness checks.

This survey data has panel components because one-third of the respondents re-participated six months later, one-third of the interviewees were never surveyed again, and one-third were participants six months earlier. However, the study periods of this paper have cross-sectional components because no one re-participated again during five months.

The key dependent variable in the model is the response to the question:

- **Hybrid 1:** On a scale from zero to one hundred, where zero means that you would definitely not buy and one hundred means you definitely would buy, what are the chances that you might buy <u>a hybrid vehicle</u> sometime in the future?

[77] We obtained the raw data from the survey from the Inter-University Consortium for Political and Social Research (ICPSR).

- **Plug-in 1:** On a scale from zero to one hundred, where zero means that you would definitely not buy and one hundred means you definitely would buy, what are the chances that you might buy <u>a plug-in hybrid vehicle</u> sometime in the future?

The beauty of this survey is additional survey questions which include more information on the future fuel savings. With more information related to cost savings, it is plausible that a survey participant may calculate the future fuel savings better than before. It may affect the willingness to consider hybrid or plug-in hybrid vehicles. Follow-up questions are as follows:

- **Hybrid 2:** If a hybrid vehicle reduced total fuel costs by twenty-five percent and the vehicle itself costs one thousand five hundred dollars more than an ordinary vehicle, what are the chances that you might buy a hybrid vehicle, using the same scale ranging from zero to one hundred, where zero means that you would definitely not buy and one hundred means you definitely would buy sometime in the future?
- **Plug-in 2:** If a plug-in hybrid reduced total fuel costs by seventy-five percent and cost two thousand five hundred dollars more than an ordinary vehicle, what are the chances you might buy the <u>plug-in hybrid</u>, using the scale ranging from zero to one hundred, where zero means you would definitely not buy and one hundred means you definitely would buy?
- **Plug-in 3:** What if a plug-in hybrid that reduced total fuel costs by seventy-five percent cost five thousand dollars more than an ordinary vehicle, what are the chances you might buy the <u>plug-in hybrid</u>, using the scale ranging from zero to one hundred, where zero means that you would Definitely not buy and one hundred means you definitely would buy?

- **Plug-in 4:** What if a plug-in hybrid that reduced total fuel costs by seventy-five percent cost ten thousand dollars more than an ordinary vehicle, what are the chances you might buy the plug-in hybrid, using the scale ranging from zero to one hundred, where zero means that you would Definitely not buy and one hundred means you definitely would buy?

Table 25 shows summary statistics for the entire questionnaires. The dependent variable is the likelihood of buying a hybrid or plug-in hybrid vehicle. The event is considered as a probability that an individual would buy these vehicles. If we compare Hybrid 1 and Plug-in 1, survey participants would prefer a hybrid to a plug-in hybrid vehicle. As one might guess, participants who answered while having received the more precise information on future gasoline price were slightly more likely to buy hybrid vehicles. Once more information on future gasoline prices was given to respondents of the plug-in hybrid vehicle question, the probability of buying plug-in hybrid vehicles increased. Among Plug-in 2 and Plug-in 4 questionnaires, the likelihood of buying a plug-in hybrid vehicle decreased.

Table 25. Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent Variables					
V1208_mod (Hybrid 1)	1,222	0.623257	0.304363	0	1
V1209_mod (Hybrid 2)	1,222	0.667177	0.280539	0	1
V1210_mod (Plug-in 1)	1,222	0.566776	0.286625	0	1
V1211_mod (Plug-in 2)	1,222	0.630655	0.258926	0.01	1
V1212_mod (Plug-in 3)	1,222	0.438175	0.25384	0.01	1
V1213_mod (Plug-in 4)	1,222	0.203429	0.232507	0	1
Independent Variables					
E_PX5	1,222	1.875614	1.35781	1	5
E_PX1	1,222	2.230769	1.38936	1	5
Gasoline Price	1,222	3.422274	0.68121	2.012992	4.278
AGE	1,222	49.28969	14.15595	18	91
AGESQ	1,222	2629.7	1437.682	324	8281
GENDER	1,222	1.518003	0.49988	1	2
RACE	1,222	1.256137	0.760851	1	5
NUMADT	1,222	1.968085	0.71703	1	6
NUMKID	1,222	0.774141	1.133101	0	8
MARRY	1,222	1.923077	1.476202	1	6
ENVIRONMENTALISM	1,222	1.729133	1.00014	1	5
LOCATION_PARKING	1,222	2.743863	1.541357	1	6
Log(income)	1,222	11.22614	0.750458	8.36637	13.81551
TYPES OF VEHICLES	1,222	2.052373	1.26201	1	4
VEHNUM	1,222	2.279869	1.126803	1	13
AVG. MILES DRIVEN/DAY	1,222	32.71931	35.74304	1	400

*The current gasoline price: U.S. monthly retail gasoline and diesel Prices including taxes (dollars per gallon).[78]

The key independent variable is the current gasoline price. We use the monthly retail gasoline and diesel Prices including taxes (dollars per gallon).[79] Since there is Census Division information in the survey data, we can match between EIA region and Census division using

[78] http://www.eia.gov/dnav/pet/pet_pri_gnd_a_epm0u_pte_dpgal_m.htm
[79] http://www.eia.gov/dnav/pet/pet_pri_gnd_a_epm0u_pte_dpgal_m.htm

Table 32. If Census division includes multiple EIA regions, we take the average of gasoline prices. For example, Census region 5 includes both PADD 1B and PADD 1C so that we take the average gasoline price of each EIA region. We use the survey month and year as a matching criterion in Table 33 includes monthly retail gasoline and diesel prices per EIA region.

When it comes to the monthly average future gasoline price perception, there is a clear distinction between the average price expectation of five years and one year. It is arguable whether the expected gasoline price is in nominal or real terms. Anderson et al. (2013) assume that respondents answer in nominal terms. Figure 18 illuminates the decreasing trend of the one-year average price expectation as parallel with the current gasoline price. On the contrary, the average of the five-year gasoline price perception was relatively flat. In the long run, consumers tended to have a relatively constant future price expectation even if the price plummeted. To obtain the expected future gasoline perception for one-year and five-year, we added the current gasoline price and the average price expectation of five years and one year, as below:[80]

$$E(P_{i,t+1}) = P_{i,t} + Expectation_{s,t+1} \tag{9}$$

$$E(P_{i,t+5}) = P_{i,t} + Expectation_{s,t+5} \tag{10}$$

Where i indicates a household and t indicates time

[80] Attari (2010) adpoted the multilevel regression model to estimate participants' perceptions on energy usage/savings as a function of actual energy usage/savings.

To put gasoline prices and the level of gasoline prices into a common unit, we multiply by Consumer Price Index (CPI) using a base period as for July 2008.[81] Among different CPIs, we use “cuur0000sa0l1e: All items less food and energy.”

shows the correlation among gasoline prices. There is a significant correlation between the current gasoline price and the expected future gasoline belief so that we run the below econometric model separately.

4.2.2 Model Specifications

First, we run the Ordinary Least Square (OLS) regression and check the in-sample prediction. Since the dependent variable ranges from 0 to 1, the predicted values of the OLS are out of the range 0-1. So, we use non-linear models to estimate the constructed models. If we use a logit or probit model, we need to convert a dependent variable to a binary variable. There is no reason to discard information.

For a proportional dependent variable data, we use generalized linear models (GLM) with a log-link relationship (McCullagh & Nelder, 1989)[82]. Table 5 shows the coding mechanism of independent variables. We construct a model as below:

$$E(buying|X_{i,1,,\dots\dots\dots}X_{i,t}) = \beta_0 + \beta_1 K_{i,t} + \beta X_{i,t} + u_{i,t} \tag{11}$$

[81] http://data.bls.gov/cgi-bin/surveymost?cu

[82] Papke and Wooldridge (1996) suggested direct models for solving the above issue by applying the method of quasi-maximum likelihood estimation (QMLE). So we can use a fractional probit model to obtain consistent estimators of the efficient conditional mean parameters. However, we do not use it because the dependent variables are not generated from aggregated binary variables. http://www.stata.com/manuals14/rfracreg.pdf

Where i indexes a household and t indexes month. $\boldsymbol{K_{i,t}}$ indicates $\boldsymbol{P_{i,t,}}$ $\boldsymbol{E(P_{i,t+1})}$, $\boldsymbol{E(P_{i,t+5})}$ in (1) and (2), $\boldsymbol{X_{i,t}}$ indicates a vector of control variables: Age, Gender, Race, Number of Adults, Number of Kids, Marry, Environmentalism, Recharge at home/no, need to go gas station, Parking location, Log(Income), Type of Vehicles, Number of Vehicles, Average Miles Driven per day. $\boldsymbol{u_{i,t}}$ indicates residuals.

Another important aspect of this study lies in its attempt to estimate the effect of regional differences in the willingness to purchase hybrid/plug-in hybrid vehicles. This is a legitimate argument that people experience different incentives for hybrid/plug-in hybrid vehicles which may affect an individual's likelihood to buy a more fuel-efficient car. Therefore, we control for time-invariant regional dummies.

We used the Survey (Svy) command in STATA to create the design elements of the survey because the national sampling of dwelling units was selected by area probability sampling. The household weights were used to yield a representative sample of all households. The population was partitioned into crossing census divisions by MSA/non-MSA strata. Additionally, we consider "n/a" responses as missing values and dropped them. In order to fill nonresponses, we used a multiple imputation method. In the robustness checks, we dropped nonresponses.

Table 26. Coding of Independent Variables

Variable	Coding
Gas Prices up/down next 5 years	Go up (1), Stay the same (3), Go down (5)
Gas Prices up/down next 1 years	Go up (1), Stay the same (3), Go down (5)
The Current Gasoline Price	$/gallon
Age	18-91 years old
Gender	Male (1), Female (2)
Race	White (1), Black (2), Hispanic (3), African Indian/Alaskan native (4), Asian/Pacific Islander (5)
Number of Adults	1-6
Number of Kids	0-8
Marry	Married (1), Separated (2), Divorced (3), Widowed (4), Never Married (5), Married, but spouse away in service (6), NA (9)
Environmentalism	Very important (1), somewhat important (2), neither (3), not very important (4), not at all important (5)
Parking location	Attached garage (1), unattached garage (2), carport (3), driveway or lot (4), street (5), nearby lot or structure (6)
Log(Income)	$4,300-$999,995 or more (current dollars)
Type of Vehicle	Car (1), pickup/truck (2), van (3), SUV (4)
Number of Vehicles	1-13
Avg. Miles Driven per day	1-400 miles

4.3 Estimation Results

Table 27 shows hybrid vehicle estimation results. First, column (4) shows significant results of gasoline prices' effect on the willingness to buy hybrid vehicles once more information is given to a participant at the 0.05 significance level. Second, column (6) indicates significant results of five-year future perception on the willingness to buy hybrid vehicles at the 0.05 significance level. Third, column (1) and (3) show the effect of both five-year future perception and the current gasoline price are only significant at the 10% level. We could argue that when more information on fuel saving of a hybrid vehicle is provided to a participant, we can have a statistically significant finding.

Table 28 shows the estimation results on plug-in hybrid vehicle. We did not find any evidence to support either the current gasoline price's or future gasoline price perception's effect on the likelihood of buying plug-in hybrid vehicles. A possible explanation is that it is due to a systematic difference between hybrid vehicles and plug-in hybrid vehicles. Unlike hybrid vehicles, plug-in hybrid vehicles also use rechargeable batteries, which make them less reliant on gasoline. So it is plausible that consumers are less resilient to the gasoline price changes' or the future price perception's effect on the willingness to buy plug-in hybrid vehicles.

Table 29 shows marginal effects. Column (1) shows 1% that a decrease of gasoline price decreases the probability of buying a hybrid vehicle by 15.1 %, holding the other variables at their means. The most salient factor is that the magnitude of five-year and one-year future gasoline price beliefs are lower than the current gasoline price. So, if we assume a no-change forecast of future gasoline price, it overestimates the effect of gasoline price.

Table 27. Estimation Results (Hybrid Vehicles)

VARIABLES	GLM V1208_mod	GLM V1208_mod	GLM V1208_mod	GLM V1209_mod	GLM V1209_mod	GLM V1209_mod
gasolineprice	0.123*			0.151**		
	(0.0711)			(0.0717)		
E_PX1		0.0615			0.0676*	
		(0.0402)			(0.0407)	
E_PX5			0.103*			0.139**
			(0.0624)			(0.0631)
AGE	0.0298	0.0285	0.0300	0.0455**	0.0440**	0.0457**
	(0.0190)	(0.0190)	(0.0190)	(0.0191)	(0.0191)	(0.0191)
AGESQ	-0.000433**	-0.000420**	-0.000433**	-0.000587***	-0.000573***	-0.000587***
	(0.000177)	(0.000177)	(0.000177)	(0.000179)	(0.000179)	(0.000179)
V1625	0.0431	0.0370	0.0401	0.0412	0.0338	0.0375
	(0.0976)	(0.0977)	(0.0976)	(0.0987)	(0.0987)	(0.0987)
RACE	-0.00519	-0.00567	-0.00499	-0.0442	-0.0450	-0.0438
	(0.0462)	(0.0462)	(0.0462)	(0.0466)	(0.0466)	(0.0466)
NUMADT	-0.0587	-0.0601	-0.0570	-0.0828	-0.0836	-0.0811
	(0.0791)	(0.0792)	(0.0791)	(0.0796)	(0.0797)	(0.0796)
NUMKID	0.0232	0.0225	0.0229	0.0203	0.0196	0.0200
	(0.0207)	(0.0203)	(0.0206)	(0.0198)	(0.0194)	(0.0197)
MARRY	0.00695	0.00643	0.00945	-0.00700	-0.00735	-0.00384
	(0.0371)	(0.0371)	(0.0371)	(0.0374)	(0.0374)	(0.0374)
V1219	-0.288***	-0.286***	-0.288***	-0.300***	-0.299***	-0.300***
	(0.0412)	(0.0412)	(0.0412)	(0.0412)	(0.0413)	(0.0413)
V1216	0.00697	0.00657	0.00576	-0.000972	-0.00104	-0.00286
	(0.0331)	(0.0332)	(0.0332)	(0.0335)	(0.0335)	(0.0335)
income_ln	0.287***	0.297***	0.294***	0.338***	0.349***	0.347***
	(0.0701)	(0.0702)	(0.0701)	(0.0707)	(0.0708)	(0.0708)
V1111	-0.00628	-0.00705	-0.00666	-0.0156	-0.0167	-0.0159
	(0.0352)	(0.0352)	(0.0352)	(0.0357)	(0.0356)	(0.0357)
VEHNUM	-0.0160	-0.0155	-0.0159	-0.00640	-0.00574	-0.00626
	(0.0179)	(0.0179)	(0.0178)	(0.0166)	(0.0166)	(0.0166)
V1201	-2.76e-05	-2.81e-05	-3.15e-05	-0.000177	-0.000178	-0.000183
	(0.000224)	(0.000224)	(0.000224)	(0.000227)	(0.000227)	(0.000227)
Constant	-3.029***	-2.897***	-3.063***			
	(1.023)	(1.011)	(1.030)			
Constant				-3.789***	-3.591***	-3.880***
				(1.034)	(1.021)	(1.043)
REGION FE	YES	YES	YES	YES	YES	YES

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 28. Estimation Results (Plug-in Hybrid Vehicles)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
gasolineprice	0.0247			0.0139			0.00921			0.0342		
	(0.0721)			(0.0727)			(0.0812)			(0.105)		
E_PX1		-0.00207			-0.0171			-0.00588			-0.00301	
		(0.0404)			(0.0407)			(0.0462)			(0.0597)	
E_PX5			0.0308			0.0183			0.00580			0.000335
			(0.0631)			(0.0635)			(0.0714)			(0.0921)
AGE	0.0367*	0.0367*	0.0367*	0.0382*	0.0386**	0.0382*	-0.000169	-0.000218	-0.000180	-0.00748	-0.00772	-0.00775
	(0.0194)	(0.0194)	(0.0194)	(0.0195)	(0.0195)	(0.0195)	(0.0223)	(0.0223)	(0.0223)	(0.0288)	(0.0288)	(0.0288)
AGESQ	-0.000449**	-0.000450**	-0.000450**	-0.000522***	-0.000526***	-0.000522***	-0.000129	-0.000128	-0.000129	-7.99e-06	-5.26e-06	-5.01e-06
	(0.000182)	(0.000182)	(0.000182)	(0.000184)	(0.000184)	(0.000184)	(0.000215)	(0.000215)	(0.000215)	(0.000282)	(0.000282)	(0.000282)
V1625	-0.0978	-0.0982	-0.0984	-0.148	-0.147	-0.148	0.0188	0.0186	0.0186	0.0233	0.0224	0.0224
	(0.0986)	(0.0986)	(0.0986)	(0.0994)	(0.0994)	(0.0993)	(0.110)	(0.110)	(0.110)	(0.141)	(0.141)	(0.141)
RACE	0.0127	0.0122	0.0130	0.00680	0.00614	0.00698	0.0401	0.0398	0.0401	0.106*	0.106*	0.106*
	(0.0477)	(0.0477)	(0.0477)	(0.0479)	(0.0479)	(0.0479)	(0.0506)	(0.0505)	(0.0506)	(0.0575)	(0.0575)	(0.0575)
NUMADT	0.00514	0.00622	0.00517	-0.0252	-0.0231	-0.0253	0.000957	0.00155	0.00106	0.0482	0.0495	0.0492
	(0.0832)	(0.0832)	(0.0832)	(0.0803)	(0.0803)	(0.0803)	(0.0874)	(0.0875)	(0.0874)	(0.108)	(0.108)	(0.108)
NUMKID	0.00979	0.00965	0.00979	0.00643	0.00627	0.00643	0.00905	0.00896	0.00902	-0.00523	-0.00547	-0.00545
	(0.0147)	(0.0147)	(0.0147)	(0.0145)	(0.0145)	(0.0145)	(0.0142)	(0.0142)	(0.0142)	(0.0252)	(0.0253)	(0.0253)
MARRY	-0.0118	-0.0114	-0.0112	-0.0205	-0.0198	-0.0201	-0.00666	-0.00647	-0.00653	0.00275	0.00317	0.00310
	(0.0374)	(0.0374)	(0.0374)	(0.0375)	(0.0376)	(0.0375)	(0.0417)	(0.0417)	(0.0417)	(0.0527)	(0.0528)	(0.0527)
V1219	-0.197***	-0.197***	-0.197***	-0.210***	-0.211***	-0.210***	-0.103*	-0.103*	-0.103*	-0.146**	-0.146**	-0.146**
	(0.0467)	(0.0467)	(0.0467)	(0.0466)	(0.0466)	(0.0466)	(0.0546)	(0.0546)	(0.0546)	(0.0735)	(0.0736)	(0.0736)
V1218	-0.314***	-0.314***	-0.314***	-0.345***	-0.345***	-0.344***	-0.145**	-0.146**	-0.145**	-0.0968	-0.0975	-0.0974
	(0.0578)	(0.0578)	(0.0578)	(0.0580)	(0.0580)	(0.0580)	(0.0739)	(0.0739)	(0.0739)	(0.101)	(0.101)	(0.101)
V1216	-0.0151	-0.0143	-0.0157	-0.0168	-0.0155	-0.0171	-0.0197	-0.0191	-0.0196	-0.0257	-0.0245	-0.0247
	(0.0333)	(0.0333)	(0.0334)	(0.0336)	(0.0337)	(0.0337)	(0.0370)	(0.0370)	(0.0370)	(0.0473)	(0.0473)	(0.0473)
income_ln	0.197***	0.198***	0.199***	0.295***	0.294***	0.296***	0.189**	0.188**	0.189**	0.156	0.156	0.156
	(0.0707)	(0.0708)	(0.0707)	(0.0714)	(0.0715)	(0.0714)	(0.0796)	(0.0797)	(0.0796)	(0.102)	(0.102)	(0.102)
V1111	0.0117	0.0112	0.0117	-0.00264	-0.00311	-0.00258	-0.00965	-0.00977	-0.00969	-0.000718	-0.00129	-0.00123
	(0.0357)	(0.0357)	(0.0357)	(0.0359)	(0.0359)	(0.0359)	(0.0395)	(0.0395)	(0.0395)	(0.0503)	(0.0503)	(0.0503)
VEHNUM	-0.0387	-0.0385	-0.0388	-0.0192	-0.0189	-0.0192	-0.0149	-0.0148	-0.0149	-0.00933	-0.00910	-0.00912
	(0.0382)	(0.0382)	(0.0382)	(0.0217)	(0.0217)	(0.0217)	(0.0237)	(0.0237)	(0.0237)	(0.0243)	(0.0243)	(0.0243)
V1201	-0.000411*	-0.000410*	-0.000412*	-0.000226	-0.000225	-0.000227	-4.89e-05	-4.88e-05	-4.89e-05	-0.000196	-0.000195	-0.000195
	(0.000239)	(0.000239)	(0.000240)	(0.000237)	(0.000236)	(0.000237)	(0.000272)	(0.000272)	(0.000272)	(0.000371)	(0.000371)	(0.000371)
Constant	-1.769*	-1.681*	-1.817*	-2.371**	-2.255**	-2.402**	-1.639	-1.578	-1.633	-2.349	-2.211	-2.227
	(1.033)	(1.020)	(1.040)	(1.040)	(1.028)	(1.048)	(1.162)	(1.147)	(1.172)	(1.494)	(1.473)	(1.507)
REGION FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 29. Marginal Effects[83] (Hybrid Vehicles)

VARIABLES	(1) Marginal effects	(2) Marginal effects	(3) Marginal effects
Gasoline price	0.151**		
	(0.0717)		
E_PX1		0.0676*	
		(0.0407)	
E_PX5			0.139**
			(0.0631)
Constant	-3.789***	-3.591***	-3.880***
	(1.034)	(1.021)	(1.043)

1. Standard errors in parentheses
2. *** p<0.01, ** p<0.05, * p<0.1

As a robustness check, we dropped "don't' know" answers and performed multiple imputation to fill the remaining missing portion of the data. We found consistent results that there was a significant result in the Hybrid 2 questionnaire.

The modeling results also indicate a statistically significant effect of environmentalism. Several studies found that a pro-environmental attitude is positively related to purchasing environmentally friendly vehicles (Gadenne, Sharma, Kerr, & Smith, 2011). Environmentalists are more likely to protect the environment, even if they have to pay a few extra dollars for the initial purchase of an eco-friendly car. It has been empirically proven that environmentalists are more likely than non-environmentalists to buy hybrid vehicles (M. E. Kahn, 2007) and electric vehicles (Hidrue, Parsons, Kempton, & Gardner, 2011). According to Deloitte (2011), a green lifestyle positively affects the intention to purchase electric vehicles. Recent surveys found that environmentally friendly and tech-savvy consumers are more interested in purchasing electric

[83] The average marginal effect follows the same pattern.

vehicles (Deloitte, 2011). This argument can be extended to “lifestyle theory”(Walker & Li, 2007; Axsen, Bailey, & Castro, 2015) which affects alternative-vehicle choice.

We also find that a charging station at home is a significant factor, which is consistent with previous literature (Yamashita, Miimura, Takamori, Wang, & Yokoyama, 2013). Most literature regarding the willingness to buy plug-in hybrid vehicles concentrate on the limitation of plug-in hybrid vehicles such as limited driving range. For example, most electric vehicles can only go about 100 miles before needing to be recharged, and fully recharging the battery 4-8 hours (U.S. EPA, 2012). Seminal studies about limitations of electric vehicles were conducted by Calfee (1985) and Beggs (1981). Both studies established concern over the vehicle’s maximum driving range as the primary obstacle to adopting electric vehicles. Subsequently, Bunch, Bradley, and Golob (1993), and Brownstone, Bunch, and Train (2000) concluded that limited driving range, long charging time, and high initial vehicle price were the primary barriers for consumers. More recently, Singer (2016) found that 56 % of survey respondents are willing to purchase electric vehicles if an electric vehicle could travel 300 miles on a single charge.

Needlessly to say, young and higher income leads to higher likelihood of buying more fuel-efficient cars. This is also consistent with previous studies. Higher income leads to new and domestic vehicle purchasing, whereas those with lower incomes are more likely to purchase used and Japanese vehicles (Roorda, Mohammadian, & Miller, 2000). Additionally, lower-income people are more apt to buy small cars while people with higher incomes are associated with luxury vehicles, minivans, and SUVs (Sports Utility Vehicles). This is an important policy implication since lower and unevenly distributed income is an obstacle to the adoption of more fuel-efficient cars (Erdem, Şentürk, & Şimşek, 2010).

Additionally, younger drivers are more likely to drive small cars, middle-aged people are more apt to select minivans and pickups, and older people are more liable to choose large and luxury vehicles. In particular, younger male consumers prefer electric vehicles (Ziegler, 2010).

The limitation of this research is that we could not test how long the gasoline price takes to diffuse to consumers because we only had one-year and five-year future price expectations compared to the current price. It would be interesting to test the argument of the delayed diffusion of "sticky information" (Mankiw & Reis, 2002).

4.4 Payback Periods

It is hard to calculate the precise amount of lifetime fuel cost savings as indicated in Sallee (2013). Consumers should consider the following future fuel cost savings:

$$Present\ discounted\ value\ of\ lifetime\ fuel\ costs = \sum_{t=0}^{T} \delta^t \frac{P \times m}{mpg} \qquad (12)$$

Where t=0 indicates today, T is the lifespan of the vehicle, $\delta$is the discount rate, P is the price of gasoline per gallon, m is the number of miles driven, mpg is miles per gallon.

As Sallee (2013) addressed, many people do not know which discount rate they employ, the number of miles driven, etc. Even if consumers have full information on the above variables, it is not easy to calculate the lifetime fuel costs when they take a survey. To make matters worse, people usually pay less attention when completing survey questionnaires. Therefore, a full calculation of the above equation seems impossible.

Sixty households in California illustrate no evidence of an economically rational decision-making process regarding fuel economy (Kurani & Turrentine, 2004). Nine out of sixty households stated that they account for fuel economy when they purchase a new car. None of them has tried to do a quantitative analysis about future fuel cost saving. It implies that personal decisions toward buying a vehicle about fuel economy are not based on sound rational decision. It is often rational for consumers to pay limited attention to energy efficiency when they purchase energy durable goods (Sallee, 2013).

Allcott and Wozny (2009) argued that consumers underestimate future gas costs when they purchase an automobile. Their finding is that consumers' underestimation of future gasoline cost implies that people truly care less about the future fuel savings when they buy a car. Allcott and Wozny (2009) failed to provide the reason why certain groups of people are less likely to be influenced by the future cost of gasoline when they purchase new vehicles. Sallee (2013) suggested the idea of rational inattention in energy economics and made a valuable contribution to the idea of rational inattention, particularly in the automobile market. However, it is still arguable that rational inattention is a subset of the notion of bounded rationality. Also, Larrick and Soll (2008) showed that U.S. consumers believe that equal increases in MPG are the same in gas savings which is called as the MPG illusion. While both MPG and Gallon Per Miles (GPM) convey useful information to consumers, GPM is more useful when consumers are buying a car because it can better capture fuel consumption information than MPG.

Possible explanations for why people usually underestimate future gasoline costs when they purchase a new vehicle are 1) consumers put little value in the future; 2) for consumers who are not interested in fuel economy, because fuel economy is bundled with another attribute of cars, consumers are uncertain that the fuel savings are represented correctly. In standard economic modeling, we typically assume exponential discounting; people discount the future prices at a constant fraction. However, the discount rate is the problem of choice, as it may differ from person to person. When we compare the total lifetime cost of a more fuel-efficient vehicle with a conventional vehicle, the selection of the discount rate is significant. Taking into consideration the typical three-year payback period of a new automobile, a 30~40% discount rate is a reasonable assumption for comparing the cost of both vehicles.

Given these constraints, people may be forced to rely on rough information provided in the survey questionnaires. Participants may think as if they are rational given the limited information provided. For example, hybrid 2 survey question allows people to roughly calculate the future fuel savings by providing the following information:

- A hybrid vehicle reduced total fuel costs by twenty-five percent
- Cost of vehicle: one thousand five hundred dollars more than an ordinary vehicle

The current year's fuel saving can be calculated by assuming 13,476 miles driven per year.[84] According to the U.S. Department of Transportation Federal Highway Administration (FHWA), Americans drive 13,476 miles per year on average. The number of years driven is assumed to be 12 years.[85] Note that the cost of the vehicle is $1,500 more than the conventional vehicle. Assume that miles per gallon (MPG) is 29 based on the least powerful non-hybrid Civic (1.81 engine) (Kelly Sims Gallagher & Muehlegger, 2011). When it comes to a discount rate, Hausman (1979) estimates that consumers use a 20% discount rate when they purchase

[84] http://cars.lovetoknow.com/about-cars/how-many-miles-do-americans-drive-per-year
[85] http://www.cnbc.com/2015/07/28/americans-holding-onto-their-cars-longer-than-ever.html

energy durable goods. So, we assume 3%, 5%, 10%, 15%, and 20% discount rates, respectively, to show the sensitivity of results. Dreyfus & Viscusi's (1995) estimated discount rate in an automobile is 11%~17%. It is within the range of the above assumption. Payback periods of a hybrid vehicle are calculated as below.

Given the uncertainty in these findings, Table 30 shows payback periods based on different discount rate assumptions. If consumers form beliefs on future gasoline price, the average payback periods of beliefs are less than the current gasoline price's payback periods. So, if we assume no change to the future forecast assumption, we are likely to overestimate payback periods which in turn underestimate the likelihood of buying hybrid vehicles. Therefore, we need to be careful about estimating the likelihood of buying a hybrid vehicle concerning future gasoline price assumptions in economic models, particularly during periods of financial crisis, consistent with Anderson et al. (2013).

Table 30. Payback Periods (Hybrid Vehicle)

	Discount Rates	Average Payback Periods
The Current Gasoline Price	0.03	3.84
	0.05	3.76
	0.1	3.57
	0.15	3.37
	0.2	3.17
Expected one-year future gasoline price	0.03	3.55
	0.05	3.47
	0.1	3.3
	0.15	3.11
	0.2	2.93
Expected five-year future gasoline price	0.03	3.62
	0.05	3.58
	0.1	3.39
	0.15	3.2
	0.2	3.01

4.5 Discussion and Conclusions

It is plausible that consumers form beliefs about future gasoline price based on the current price, and it matters in terms of on the likelihood of buying hybrid cars based on rational and cognitive thinking processes. This paper tests this hypothesis by utilizing Michigan Consumer Survey data. We find statistical evidence to support the relationship between gasoline price and the willingness to buy more hybrid cars. We also find statistically significant evidence of the long-term future gasoline price beliefs on considering hybrid vehicles.

This finding has important policy implications related to taxation. This is because the gasoline tax’s effectiveness depends on whether people respond to the gasoline price change. Of course, this is a stated preference study, and state preferences have a tenuous relationship with actual purchasing decisions. Still, it suggests the gasoline tax, which internalizes negative externalities are preferable to the Corporate Average Fuel Economy (CAFÉ) standards. The most obvious policy to spur the future adoption of more fuel-efficient cars would be to increase the gasoline tax. It is not a surprising finding because it is well known that standards are less efficient than fuel taxes (Anderson & Sallee, 2016).

Energy policy scholars, including behavioral technology analysts may disagree with the fundamental assumption that we made in this paper. They may argue that consumers' decision-making is far from a rational preference maximization and that consumers do not form an explicit belief.[87] This is an open-ended question to both groups of scholars: economists and behavioral researchers. At least, the current consensus on the energy policy community is to adopt insights from as many behaviorist as possible (H. Allcott & Mullainathan, 2010; Thaler & Sunstein, 2008).

The evidence that we show in this paper is based on the assumption that we live in a world of decreasing gasoline prices. It is a bit challenging to generalize this finding to the context of increasing the gasoline price world because the financial crisis of 2008 could be an important factor to consider. It is legitimate to ask what would happen when the price of gasoline increases. People can behave either similarly or differently. This is an unanswered question, and which can be addressed in future research.

[87] This never-ending discussion is well summarized in Sanstad and Howarth's (1994) paper.

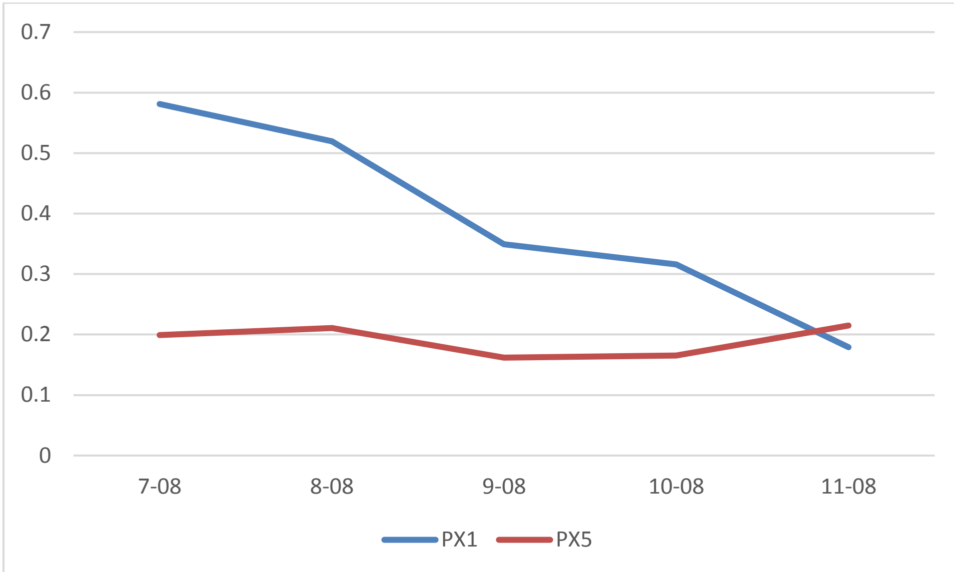

Figure 17. △Expected Future Gasoline Price

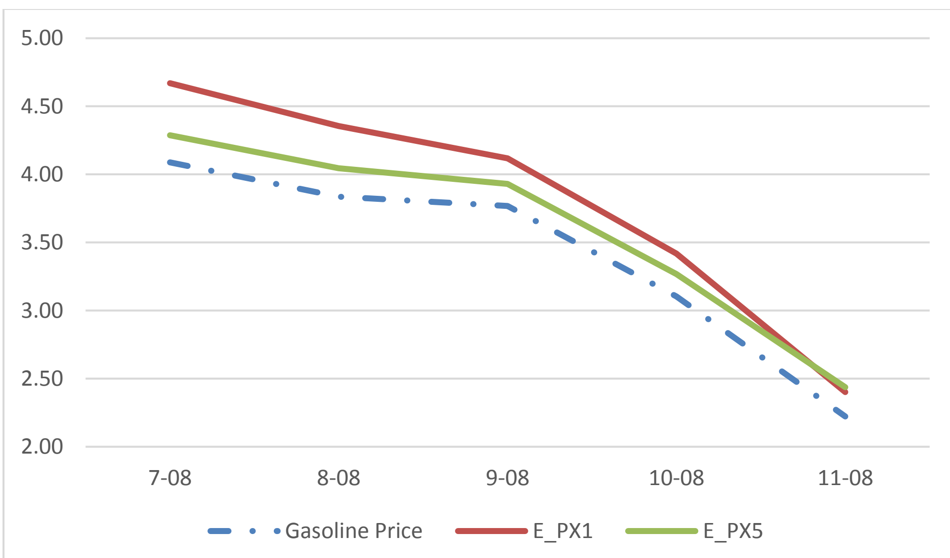

Figure 18. Gasoline price vs. Expected one-year future price vs. Expected five-year future price

Table 31. Correlation Matrix

	Gasoline price	E_PX1	E_PX5
Gasoline price	1		
E_PX1	0.6957*	1	
	0		
E_PX5	0.8775*	0.7489*	1
	0	0	
No. of Obs.	1260	1260	1260

1. Significant at 95% *

Table 32. EIA region and Census Division

States	**EIA_region**	**States**	**AB**	**Census Division**
Connecticut	PADD 1A	Connecticut	CT	1
Massachusetts	PADD 1A	Massachusetts	MA	1
Maine	PADD 1A	Maine	ME	1
New Hampshire	PADD 1A	New Hampshire	NH	1
Rhode Island	PADD 1A	Rhode Island	RI	1
Vermont	PADD 1A	Vermont	VT	1
New Jersey	PADD 1B	New Jersey	NJ	2
New York	PADD 1B	New York	NY	2
Pennsylvania	PADD 1B	Pennsylvania	PA	2
Illinois	PADD 2	Illinois	IL	3
Indiana	PADD 2	Indiana	IN	3
Michigan	PADD 2	Michigan	MI	3
Ohio	PADD 2	Ohio	OH	3
Wisconsin	PADD 2	Wisconsin	WI	3
Iowa	PADD 2	Iowa	IA	4
Kansas	PADD 2	Kansas	KS	4
Minnesota	PADD 2	Minnesota	MN	4
Missouri	PADD 2	Missouri	MO	4
North Dakota	PADD 2	North Dakota	ND	4
Nebraska	PADD 2	Nebraska	NE	4
South Dakota	PADD 2	South Dakota	SD	4
District of Columbia	PADD 1B	District of Columbia	DC	5
Delaware	PADD 1B	Delaware	DE	5
Maryland	PADD 1B	Maryland	MD	5
Florida	PADD 1C	Florida	FL	5
Georgia	PADD 1C	Georgia	GA	5

Table 32 continued

North Carolina	PADD 1C	North Carolina	NC	5
Virginia	PADD 1C	Virginia	VA	5
West Virginia	PADD 1C	West Virginia	WV	5
South Carolina	PADD 1C	South Carolina	SC	5
Kentucky	PADD 2	Kentucky	KY	6
Tennessee	PADD 2	Tennessee	TN	6
Alabama	PADD 3	Alabama	AL	6
Mississippi	PADD 3	Mississippi	MS	6
Oklahoma	PADD 2	Oklahoma	OK	7
Arkansas	PADD 3	Arkansas	AR	7
Louisiana	PADD 3	Louisiana	LA	7
Texas	PADD 3	Texas	TX	7
New Mexico	PADD 3	New Mexico	NM	8
Colorado	PADD 4	Colorado	CO	8
Idaho	PADD 4	Idaho	ID	8
Montana	PADD 4	Montana	MT	8
Utah	PADD 4	Utah	UT	8
Wyoming	PADD 4	Wyoming	WY	8
Arizona	PADD 5	Arizona	AZ	8
Nevada	PADD 5	Nevada	NV	8
California	PADD 5	California	CA	9
Oregon	PADD 5	Oregon	OR	9
Washington	PADD 5	Washington	WA	9
Alaska	PADD 5	Alaska	AK	9
Hawaii	PAD 5	Hawaii	HI	9

Table 33. Monthly Retail Gasoline and Diesel Prices (Dollars per Gallon, including taxes)

Date	PADD 1 East Coast All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)	PADD 1A New England (PADD 1A) All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)	PADD 1B Central Atlantic (PADD 1B) All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)	PADD 1C Lower Atlantic (PADD 1C) All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)	PADD 2 Midwest All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)	PADD 3 Gulf Coast All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)	PADD 4 Rocky Mountain All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)	PADD 5 West Coast All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)	PADD 5 West Coast (PADD 5) Except California All Grades Conventional Retail Gasoline Prices (Dollars per Gallon)
Jul-2008	4.085	4.111	4.148	4.063	3.994	3.992	4.132	4.278	4.278
Aug-2008	3.818	3.865	3.887	3.794	3.733	3.711	3.972	4.008	4.008
Sep-2008	3.812	3.71	3.749	3.838	3.732	3.709	3.765	3.786	3.786
Oct-2008	3.215	3.141	3.239	3.212	2.913	2.963	3.192	3.305	3.305
Nov-2008	2.262	2.406	2.457	2.193	2.007	2.103	2.203	2.476	2.476

CHAPTER 5. CONCLUSIONS & FUTURE RESEARCH

This dissertation comprises three essays that explore different areas of economics of energy innovation and product diffusion. The first two essays are related to economics of energy innovation, and the third essay is about energy-efficient product diffusion. In this chapter, we review the contributions of this dissertation and discuss directions for future research.

The ultimate goal of this dissertation is to answer the following question: “Can energy efficiency policy accelerate energy innovation?” In a nutshell, the answer is yes, but it depends on the kinds of policy instruments that we indicated in the first chapter and on how appropriate energy policies are used in conjunction with one another. What we have found in this dissertation is contrary to Sachs’ claims. The third essay indicates the importance of a gasoline tax, which is one type of carbon pricing policy that creates demand for clean vehicles. In the transportation sector, carbon pricing policies are not as effective as they are in other sectors such as the electricity market. Therefore, technology push policies like CAFÉ standards are also required to force manufacturers to make more energy-efficient vehicles.

The first essay addresses whether voluntary environmental programs positively affect innovation in household appliance firms. While literature evaluating voluntary environmental programs has described mixed findings on the effectiveness of such programs, we found statistically significant evidence of the impact of the ENERGY STAR program on participating firms’ patents. The results reveal a causal relationship between the ENERGY STAR program and innovation. This chapter can contribute to the work of two groups: (a) those involved in environmental management and corporate sustainability, and (b) environmental economists.

Additionally, when we design a clean environmental policy, we can anticipate negative externality as well as positive knowledge spillover effects.

One possible avenue for future research is the crowding effects between mandatory environmental policy and voluntary environmental policy. It is plausible that increases in energy patents in response to voluntary environmental policy lead to decreases in energy patents in response to mandatory environmental policy change. Additionally, we can develop a new index of policy uncertainty that negatively affects investment and therefore innovation.

The second essay seeks to answer the innovation of CFL and LED lighting technologies across multiple countries. To increase the innovation and diffusion of more energy-efficient lighting technologies, several factors were needed. First and foremost, a policy driver was required to affect foreign and domestic inventors. Technological advances were made because of the energy-efficiency policy; global firms were forced to invest in R&D so as to produce more energy-efficient light bulbs. Because LEDs are greener than CFLs, firms have more incentive to conduct R&D in LEDs than in CFLs, as regulations are becoming more stringent. This chapter also provides evidence to support the importance of policy certainty which further encourages innovation switching from incandescent light bulbs or CFLs to LEDs and will generate energy savings and reduce greenhouse-gas emissions.

While the second essay uses a country-level unit of analysis, future areas of research can also be found in the more detailed analyses of firm-level innovation. Due to the restriction of obtaining firm-level data between 1990 and 2007, we mainly focus on country-level analysis in this essay. We collect information on financial data for a sample of firms, including total assets, turnover, and the number of employees from the ORBIS database of Bureau Van Dijk (BvDEP).

ORBIS[89] is a global database that integrates information held across BvDEP's company. We use the same IPC classification of lighting technologies to retrieve relevant patents. To match between PATSTAT firm names and companies listed in the ORBIS database, we employ a company name disambiguation. Building on Noailly and Smeets's (2015) novel approach, we make a distinction between small firms that file a patent in one type of technology and those that innovate in both techniques. We investigate how LED innovation occurs in either large or specialized/nascent firms. We examine factors that affect firms' decisions both at the intensive and extensive margins using difference-in-difference with a propensity score matching technique (Debaere, Lee, & Lee, 2010).

Another possibility is to test the weak and strong versions of the Porter Hypothesis. The weak version of the Porter Hypothesis holds that well established environmental regulations give a firm an incentive to develop innovative abatement technology. On the other hand, the strong version of the Porter Hypothesis suggests that environmental regulation can lead to an increase in firm competitiveness. In regard to testing the weak version of the Porter Hypothesis, Jaffe and Palmer (1997) is the seminal study that investigates the relationship between total R&D expenditures (or the number of patent applications) and pollution abatement costs. Subsequently, numerous studies have found a positive relationship between environmental regulation and innovation (Brunnermeier & Cohen, 2003; Arimura, Hibiki, & Katayama, 2008; Lanoie et al., 2011; Popp, 2003, 2006b). In addition, Lanoie, Patry, and Lajeunesse (2008) found evidence to support the strong version of the Porter Hypothesis by observing extended periods.

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[89] ORBIS has information on over 57 million public and private companies' size, revenue, turnover, and other useful firm-level information. We accessed and downloaded the data as a former student user at Texas A&M University library database on December 23, 2015. However, we can only obtain the recent ten-year firm financial information: 2007-2016

The missing component in this dissertation is the role of an institution that can shape policy decisions. For example, the U.S. government has a Department of Energy (DOE), which fosters energy innovation. The DOE was created in 1977 to deal with the oil crisis. The funding activity of the DOE follows a boom-and-bust cycle that depends on the federal government's engagement with energy issues. In particular, the Advanced Research Projects Agency-Energy (ARPA-E) was created by President Barack Obama on April 27, 2009, to promote and fund R&D for energy technologies. The agency's initial funding was $151 million. It is difficult to examine the effectiveness of this program at this moment, but the agency is a positive pathway to achieving LED innovation. Therefore, ARPA-E funding since 2009 can be interpreted as a stimulus for LED innovation.

Another important matter that is not addressed in this dissertation is the role of incandescent light bulb phase-out (i.e., EISA[90]) in inducing CFL and LED innovation. It seems that the phasing out of incandescent light bulbs in multiple countries resulted in technological advances in CFLs and LEDs. These technologies have been developed and commercialized because firms were forced to stop manufacturing incandescent light bulbs and to instead produce alternative technologies. After the incandescent light bulb phase-out, the industry observed a significant increase in ENERGY STAR-certified CFLs and LEDs, which implies innovation in lighting technologies, given that the ENERGY STAR standards have been strengthened over the course of years. For example, while only 36 LED light bulbs were eligible for ENERGY STAR certification in 2010, approximately 1,000 LED products received ENERGY STAR approval in 2012. In order to measure the impact of the EISA 2007, it is more appropriate to use the number

[90] EISA entered into law on 19 December 2007.

of ENERGY STAR products in the market as opposed to the traditional patent counts as a measure of innovation. This is because most LED patents have reached maturity. We can investigate the impact of the Energy Independence and Security Act of 2007 (EISA) in the United States, which phased out 100 W incandescent light bulbs in 2012, 75 W in 2013, and 40 W and 60 W in 2014, on lighting innovation using recent patent and firm-level data.

The final essay uses the Michigan Survey of Consumers data to examine the relationship between beliefs about the future gasoline beliefs and the willingness to purchase hybrid or plug-in hybrid vehicles. The third essay of this dissertation is a bit different from the previous two chapters in two aspects. First, the unit of analysis is a household, not a firm. Second, the nature of the research design is survey data analysis.

It is still unknown which theoretical foundation best explains the formation of beliefs about the future of gas prices. However, this chapter shows that long-term future expectations are a better predictor of willingness to buy hybrid vehicles than the short-term future gasoline price beliefs.

With respect to the dissemination of green products, researchers have focused on identifying factors that motivate the consumption of environmentally friendly products. This is in part because a better understanding of consumer preferences for energy-efficient vehicles can make policies work more efficiently and effectively. The findings in this chapter can contribute to the research of transportation policy groups and behavioral economists.

These behavioral science components of stated or revealed preference studies are an important avenue for future research. Economic studies such as discrete choice analyses can incorporate vehicle attribute changes as well as psychological variables. In other words, a discrete-choice framework allows for both economic and psychological studies. The discrete-choice model has evolved from the multinomial logit model to a nested/mixed logit model. My future research aims to the above econometric models to answer the following questions: (1) How do different types of incentive policies impact the adoption of electric vehicles? (2) How can we incorporate psychological studies into discrete-choice modeling?

APPENDIX A. RAW DATA AND ADDITIONAL ESTIMATION RESULTS

This appendix illustrates raw data used in the chapter 3.

Table 34. RD&D Budgets per GDP

RD&D Budgets per thousand units of GDP																			
PRODUCT	RD&D per thousand units of GDP																		
TIME	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
COUNTRY																			
Australia	0.24				0.24		0.23		0.28		0.21		0.21		0.18	0.35	0.24	0.26	0.27
Austria	0.11	0.07	0.12	0.10	0.13	0.14	0.14	0.13	0.14	0.14	0.13	0.11	0.14	0.13	0.11	0.14	0.13	0.16	0.11
Belgium	0.28					0.20	0.21	0.26	0.24	0.30	0.20								0.27
Canada	0.55	0.55	0.52	0.52	0.43	0.41	0.39	0.35	0.30	0.27	0.25	0.24	0.26	0.27	0.29	0.24	0.35	0.41	0.41
Denmark	0.19	0.25	0.30	0.34	0.33	0.26	0.24	0.20	0.23	0.27	0.25	0.25	0.24	0.12	0.12	0.23	0.33	0.36	0.43
Finland		0.36	0.41	0.45	0.46	0.53	0.59	0.55	0.72	0.68	0.61	0.48	0.43	0.48	0.39	0.51	0.48	0.59	0.77
France	0.47	0.44	0.43	0.39	0.39	0.36	0.41	0.38	0.38	0.39	0.44	0.40	0.29	0.50	0.49	0.44	0.45	0.45	0.45
Germany			0.28	0.21	0.21	0.16	0.14	0.15	0.13	0.14	0.09	0.13	0.13	0.12	0.17	0.16	0.17	0.17	0.17
Italy	0.66	0.57	0.51		0.27	0.25	0.25	0.23	0.20	0.20		0.21	0.22	0.22	0.21	0.20	0.17	0.23	0.22
Japan	0.90	0.82	0.80	0.81	0.83	0.88	0.89	0.90	0.84	0.86	0.86	0.86	0.86	1.04	0.93	0.85	0.84	0.83	0.79
Korea														0.15		0.42	0.37	0.46	0.52
Netherlands	0.52	0.53	0.51	0.48	0.53	0.54	0.37	0.38	0.40	0.36	0.34	0.28	0.33	0.28	0.25		0.22	0.23	0.34
New Zealand		0.03	0.03		0.06	0.04	0.05	0.05	0.05	0.06	0.06	0.06	0.07	0.08	0.08	0.09	0.08	0.10	0.12
Norway	0.45	0.44	0.48	0.49	0.44	0.41	0.32	0.28	0.25	0.24	0.30	0.25	0.25	0.26	0.24	0.27	0.28	0.32	0.35
Spain	0.15	0.10	0.22	0.17	0.15	0.15	0.13	0.12	0.12	0.09	0.08	0.08	0.07	0.06	0.07	0.05	0.05	0.06	0.07
Sweden	0.42	0.39	0.35	0.44	0.34	0.34	0.24	0.21	0.23	0.21	0.26	0.27	0.31	0.33	0.33	0.33	0.19	0.26	0.26
Switzerland	0.50	0.52	0.53	0.58	0.57	0.55	0.53	0.51	0.47	0.43	0.41	0.36	0.37	0.38	0.39	0.33	0.31	0.31	0.30
United Kingdom	0.34	0.27	0.22	0.20	0.14	0.07	0.07	0.04	0.06	0.05	0.04	0.05	0.03	0.03	0.03	0.04	0.05	0.08	0.10
United States	0.38	0.42	0.42	0.33	0.32	0.33	0.31	0.27	0.23	0.22	0.24	0.22	0.27	0.26	0.24	0.24	0.25	0.23	0.28

Table 35. Household Electricity Price

Household electricity price: Total price (USD/unit)

COUNTRY	PRODUCT	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Australia	Electricity (MWh)	71	70	74	84	73	92	71	1	77	79	79	43	83	9	80	4	68	52
Austria	Electricity (MWh)	155	69	154	25	170	96	163	43	166	39	191	54	193	89	169	30	167	85
Belgium	Electricity (MWh)	166	59	159	50	170	14	164	2	172	26	198	8	186	98	164	45	163	33
Canada	Electricity (MWh)	53	12	61	16	61	71	60	69	57	91	57	5	57	78	57	69	54	53
Denmark	Electricity (MWh)	164	47	172	85	187	35	179	80	180	43	208	61	215	38	195	26	213	7
Finland	Electricity (MWh)	102	80	101	3	94	3	80	46	88	38	108	86	110	75	100	46	97	89
France	Electricity (MWh)	150	12	141	16	153	41	146	47	150	12	166	62	163	85	133	93	129	3
Germany	Electricity (MWh)	163	80	159	32	171	84	169	11	178	43	203	0	180	36	159	30	159	33
Italy	Electricity (MWh)	156	70	172	54	182	8	145	81	164	11	169	32	177	67	159	50	159	31
Japan	Electricity (MWh)	176	80	191	8	202	89	230	26	249	44	269	48	230	10	207	27	186	72
Korea	Electricity (MWh)	96	19	98	60	103	8	101	19	106	95	112	9	110	58	96	84	68	98
Netherlands	Electricity (MWh)	117	19	114	15	119	5	112	81	115	25	135	3	147	97	129	72	127	86
New Zealand	Electricity (MWh)	54	97	56	71	55	20	58	23	67	38	78	29	87	26	88	65	70	59
Norway	Electricity (MWh)	73	34	72	95	75	47	67	66	67	46	78	43	81	33	77	74	67	0
Spain	Electricity (MWh)	189	72	198	24	211	6	176	73	176	2	194	53	190	67	163	41	154	68
Sweden	Electricity (MWh)	87	87	96	94	105	44	81	95	84	63	94	48	109	59	101	24	110	196
Switzerland	Electricity (MWh)	110	74	112	9	119	86	118	86	131	23	165	30	159	45	135	52	134	92
United Kingdom	Electricity (MWh)	118	47	129	48	135	51	115	62	121	69	127	19	125	47	125	14	120	78
United States	Electricity (MWh)	78	50	80	60	82	60	83	40	84	0	84	10	83	90	84	30	82	60

Table 36. Household Electricity Consumption Growth Rate

Electricity Consumption Growth rate_household COUNTRY	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Australia	5.23	1.83	0.18	3.37	-0.20	3.95	2.47	3.64	3.14	2.46	3.05	1.71	3.33	4.31	3.86	-1.22	1.51	3.07
Austria	3.05	6.10	1.34	2.89	-1.23	4.72	4.47	-2.22	0.45	4.88	2.30	8.33	3.21	3.26	-0.90	2.16	-0.10	-0.97
Belgium	3.95	8.05	1.75	4.17	1.27	3.52	5.07	-1.27	1.98	0.40	1.09	2.77	6.25	0.41	1.99	-2.02	-12.63	-3.81
Canada	-0.02	-0.34	2.20	0.13	0.36	-0.96	2.76	-0.56	-3.84	3.06	3.71	1.45	1.71	3.75	2.02	0.01	-2.43	7.14
Denmark	-2.33	4.81	0.73	1.20	0.93	-1.28	2.92	-2.63	-0.52	0.20	-0.67	-0.55	0.31	0.71	0.68	1.13	1.19	-2.12
Finland	8.18	7.13	1.39	2.88	4.11	-4.27	6.02	1.09	4.13	1.70	-1.68	6.80	2.94	2.32	-0.32	1.52	3.36	0.70
France	3.63	10.23	2.60	1.71	-0.22	-2.14	10.72	-1.18	3.41	3.07	1.41	4.01	-0.66	6.43	1.29	-3.42	3.50	-1.21
Germany	0.55	- 10.87	0.53	2.68	-1.24	2.12	5.48	-2.49	-0.26	0.62	-0.59	2.68	1.87	1.90	0.93	0.64	0.14	-0.99
Italy	3.44	3.70	1.94	1.21	1.08	0.39	1.32	0.84	1.35	2.43	0.65	0.72	2.28	3.27	2.42	0.55	1.01	-0.61
Japan	4.26	4.20	3.44	2.81	8.11	4.17	1.34	1.52	3.44	2.91	2.45	-0.26	3.37	-1.60	4.71	3.34	-1.23	4.08
Korea	16.87	9.85	11.88	9.73	11.03	6.59	8.26	6.11	1.22	5.07	7.29	5.68	7.82	5.43	9.07	4.65	3.27	3.15
Netherlands	3.13	3.64	2.34	2.29	3.35	6.49	1.53	2.00	1.97	2.65	2.12	1.39	3.18	2.25	0.87	2.98	2.48	-2.17
New Zealand	3.75	2.19	-2.18	0.22	1.75	1.36	3.50	-0.37	2.24	-0.13	1.56	3.02	0.59	3.56	1.75	-1.24	4.29	-1.65
Norway	4.97	7.64	0.11	0.42	3.75	1.80	1.91	-3.71	3.15	-0.01	-1.16	3.57	-3.43	-7.57	1.19	4.94	-1.06	3.87
Spain	2.33	2.26	1.67	3.04	7.45	3.50	4.24	6.90	3.98	8.98	-4.01	13.91	1.91	7.11	7.03	7.82	8.47	0.49
Sweden	0.27	8.13	-2.39	4.04	1.62	-0.30	2.20	-1.72	-0.19	-5.49	4.62	0.38	-1.68	1.27	-1.48	3.11	-2.75	-4.46
Switzerland	-0.12	4.81	2.30	0.04	0.15	3.43	4.03	-2.70	1.77	2.88	1.09	2.24	1.31	2.38	2.61	2.99	0.44	-1.30
United Kingdom	1.65	4.59	1.41	0.98	0.95	0.79	5.19	-2.84	4.74	0.82	1.39	3.12	-0.70	7.39	0.97	1.22	-0.80	-1.31
United States	2.04	3.40	-2.04	6.29	1.38	3.37	3.84	-0.62	4.83	1.52	4.15	0.86	5.20	0.84	1.27	5.20	-0.57	3.01

Table 37. GDP Growth Rate

GDP(output approach) growth rate																		
Country	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Australia	2.68	1.95	4.98	5.10	6.20	6.74	5.22	5.76	5.36	6.53	6.73	6.84	6.29	7.58	7.05	8.21	8.92	8.41
Austria	7.48	7.21	5.65	3.30	4.99	4.53	3.38	3.39	3.99	3.88	4.81	3.24	2.82	2.08	4.55	4.76	5.32	5.96
Belgium	6.04	4.76	5.01	2.99	5.39	3.63	2.00	4.56	3.75	4.25	5.70	2.98	3.50	2.80	5.70	4.29	5.21	5.41
Canada	3.51	0.89	2.36	3.96	6.07	5.04	3.47	5.44	3.92	6.95	9.61	3.34	4.06	5.32	6.52	6.47	5.40	5.31
Denmark	4.49	4.01	3.69	0.58	7.14	4.36	4.97	5.34	3.48	4.68	6.88	3.36	2.82	1.88	4.77	5.40	6.06	3.36
Finland	5.91	-4.45	-2.43	1.06	5.85	8.58	3.56	8.50	8.71	5.43	7.36	6.00	2.67	2.21	4.56	3.73	5.00	8.09
France	5.66	3.64	3.62	1.02	3.30	3.26	2.77	3.24	4.54	3.63	5.48	3.99	3.21	2.71	4.48	3.58	4.59	4.99
Germany	8.83	8.35	7.31	3.14	4.67	3.75	1.45	2.12	2.60	2.31	2.50	2.99	1.35	0.49	2.28	1.33	4.02	5.01
Italy	11.08	9.24	5.24	3.00	5.77	7.95	5.90	4.49	4.19	3.21	5.75	4.81	3.61	3.34	4.15	2.86	3.94	3.95
Japan	7.96	6.02	2.42	0.61	0.98	1.20	2.04	2.20	-2.06	-1.47	0.98	-0.85	-1.27	-0.06	0.98	0.04	0.55	1.24
Korea	20.91	20.82	14.40	13.47	18.05	17.18	12.17	10.23	-1.11	9.99	10.11	8.34	10.72	6.43	8.03	5.00	5.03	7.99
Netherlands	5.81	5.63	4.24	2.88	5.08	5.24	4.80	7.04	6.67	6.56	8.01	6.39	3.74	2.46	3.41	4.14	6.16	5.88
New Zealand	2.58	-0.21	3.12	7.97	7.12	6.22	5.06	3.67	1.92	5.99	5.84	7.40	5.16	6.89	7.00	5.56	5.16	8.30
Norway	5.82	5.36	2.91	5.20	4.89	7.34	9.50	8.22	1.92	8.81	19.13	3.76	-0.28	3.81	10.03	11.61	11.38	6.07
Spain	11.38	9.66	7.70	3.46	6.36	7.83	6.24	6.16	6.95	7.27	8.74	8.24	7.11	7.23	7.21	8.03	8.32	7.23
Sweden	10.30	7.01	-0.15	0.10	6.75	7.98	2.57	4.52	5.04	5.51	6.37	4.11	3.70	4.19	4.77	3.64	6.59	6.39
Switzerland	8.45	4.44	2.08	2.19	2.47	1.22	0.81	2.10	2.82	1.83	5.35	2.49	-0.19	1.00	3.24	3.70	6.04	6.50
United Kingdom	8.68	5.25	3.74	5.29	5.29	5.07	6.80	5.09	5.07	4.32	6.26	3.79	5.17	6.57	5.43	5.69	5.81	5.50
United States	5.69	3.25	5.92	5.19	6.25	4.86	5.69	6.28	5.58	6.29	6.46	3.28	3.35	4.86	6.64	6.67	5.82	4.49

This appendix illustrates additional triple difference-in-difference estimation results in the chapter 3.

Table 38. Triple difference-in-difference estimation results (US)

VARIABLES	(1) numberofpatent	(2) numberofpatent	(3) numberofpatent
POST_epa_US_led	-47.96	-74.19	-72.81
	(157.0)	(125.8)	(120.4)
POST_epa_led	270.3***	296.6***	295.2***
	(82.97)	(79.13)	(80.22)
US_led	73.62	73.62	73.62
	(80.60)	(75.22)	(63.13)
US	-1,314***	-826.1***	-933.9***
	(233.6)	(238.2)	(263.7)
POST_epa	-206.9**	-115.9**	-172.6*
	(92.47)	(50.60)	(100.6)
POST_epa_US	220.3*	189.1**	210.3**
	(114.2)	(89.19)	(94.95)
rdd	2.313***	1.563***	1.692***
	(0.401)	(0.403)	(0.440)
elec_price	0.447*	0.665	0.304
	(0.256)	(0.539)	(0.454)
elec_con	7.659	-1.393	-2.371
	(7.687)	(5.959)	(7.321)
gdp	40.20***	6.037	24.00
	(14.43)	(8.509)	(18.45)
Constant	-96.08**	-136.5	-76.44
	(45.70)	(95.43)	(77.43)
Observations	428	428	428
R-squared	0.458	0.538	0.551
Year FE	YES	NO	YES
Country FE	NO	YES	YES

Notes:

1. POST equals 1 after 2005
2. US indicates those whose inventor country location is United States.
3. Observations indicate the number of countries multiplied by the number of years
4. Robust standard errors in parentheses
5. *** p<0.01, ** p<0.05, * p<0.1

Table 39. Triple difference-in-difference estimation results (Korea)

VARIABLES	(1) numberofpatent	(2) numberofpatent	(3) numberofpatent
POST_epa_KR_led	337.2	341.3	341.8
	(318.0)	(355.2)	(349.2)
POST_epa_led	211.4**	207.3***	206.8***
	(85.85)	(70.21)	(70.96)
KR_led	1,053***	1,053***	1,053***
	(287.7)	(328.0)	(323.1)
KR	143.4	220.6***	136.2*
	(87.90)	(65.44)	(69.42)
POST_epa	2.014	-89.63**	-71.81
	(77.48)	(40.87)	(84.83)
POST_epa_KR	121.8	131.4***	182.8***
	(89.11)	(36.61)	(59.02)
rdd	0.908***	0.669***	0.624***
	(0.199)	(0.164)	(0.156)
elec_price	1.285***	1.900***	1.299**
	(0.397)	(0.665)	(0.567)
elec_con	2.613	-0.276	-1.412
	(7.278)	(5.737)	(7.094)
gdp	-42.08***	2.086	9.978
	(10.85)	(7.696)	(15.16)
Constant	-128.7**	-398.5***	-344.1***
	(57.13)	(131.4)	(125.1)
Observations	428	428	428
R-squared	0.399	0.583	0.592
Year FE	YES	NO	YES
Country FE	NO	YES	YES

Notes:

1. POST equals 1 after 2005
2. KR indicates those whose inventor country location is South Korea.
3. Observations indicate the number of countries multiplied by the number of years
4. Robust standard errors in parentheses
5. *** p<0.01, ** p<0.05, * p<0.1

This appendix illustrates additional negative binomial model estimation results in the chapter 2.

Table 40. Negative Binomial Estimation with fixed effects

	(1)	(2)	(3)	(4)
VARIABLES	No. of Patents	lnalpha	No. of Patents	lnalpha
ES_year	0.345***		0.788***	
	(0.130)		(0.269)	
roa	-0.0254***		-0.0103	
	(0.00671)		(0.0208)	
dta	-2.906		4.199***	
	(2.353)		(0.341)	
avgemp3years_ln	0.828		0.170	
	(0.630)		(0.136)	
avgcapx3years_ln_norm	5.74e-05		-0.00177	
	(0.000320)		(0.00148)	
elecprice	-0.00216**		-0.00486*	
	(0.000874)		(0.00254)	
Constant	-0.462	-1.022***	-0.136	0.361
	(2.224)	(0.285)	(0.865)	(0.293)
YEAR FE	NO		YES	
FIRM FE	YES		NO	
Observations	309	309	309	309

Notes:
(1), (3). Std. Err. adjusted for 8 clusters in industry
*** p<0.01, ** p<0.05, * p<0.1

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